EPA/600/R-21/044
April 2021

# Comparative Assessment of the Impacts of Prescribed Fire Versus Wildfire (CAIF): A Case Study in the Western U.S.

April 2021

Center for Public Health and Environmental Assessment
Office of Research and Development
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# FUNDING

This work was supported in part by interagency agreements with the U.S. Department of Agriculture (#92532401) and Department of the Interior (#92533501).

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# COMPARATIVE ASSESSMENT OF THE IMPACTS OF PRESCRIBED FIRE VERSUS WILDFIRE (CAIF): A CASE STUDY IN THE WESTERN U.S.

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# EXECUTIVE SUMMARY

In January 2020, the Wildland Fire Leadership Council (WFLC), an intergovernmental committee formed to support the implementation and coordination of Federal Fire Management Policy and chaired by senior leadership in the U.S. Department of Agriculture (USDA) and Department of the Interior (DOI), requested that the U.S. Environmental Protection Agency (U.S. EPA) lead an assessment that would characterize and compare the impacts of wildland fires under different fire management strategies, including prescribed fire. In this role, the U.S. EPA, in collaboration with the U.S. Forest Service (USFS), DOI, and the National Institute of Standards and Technology (NIST) conducted an assessment, focusing on the smoke impacts of prescribed fire and wildfire, while also recognizing the direct fire impacts of each, as a means to help inform future land management and fire management strategies.

*Comparative Assessment of the Impacts of Prescribed Fire Versus Wildfire (CAIF): A Case Study in the Western U.S.* consists of a qualitative and, as feasible, quantitative assessment of the air quality and health impacts of wildland fire (i.e., prescribed fire and wildfire), along with an integrated discussion of topics that are important to consider in the context of comparing different fire management strategies including:

- A conceptual framework and model for evaluating different fire management strategies
- Background information on different fire regimes, including land management practices, and the associated impacts (both beneficial and detrimental) due to fire
- A discussion of air quality monitoring as it pertains to prescribed fire and wildfire including current monitoring capabilities and resources available to obtain information on air quality measurements and pollutant concentrations
- Characterization of epidemiologic evidence of health effects, specifically within the U.S., attributed to wildfire smoke exposures along with quantitative information on public health measures that could be instituted to reduce individual and population-level exposures to wildfire smoke
- Characterization of ecological impacts attributed to wildfire smoke
- A broad overview of the direct fire impacts of wildfire with a focus on firefighter health and safety and societal impacts (i.e., economic and welfare impacts)

The qualitative discussions presented above set the stage for the main component of the assessment, which is a novel modeling analysis focusing on case study fires in the western U.S. The first case study analysis focuses on a small fire (~3,000 acres) that occurred in Oregon, the Timber Crater 6 (TC6) Fire, from July 21−26, 2018 while the second case study focuses on the Rough Fire which occurred in California from July 31−October 1, 2015 and burned significantly more acres than the TC6 Fire (~150,000 acres). Both case study fires were selected because they represented fires managed by USFS and DOI, and occurred on federal land. The TC6 Fire was selected because there is extensive data on land management, fuel treatment, prescribed fire, and wildfire activity; whereas, the Rough Fire was selected because it represented a larger fire to allow for a scaling up of the modeling approach developed for the TC6 Fire. For both case studies, hypothetical scenarios assuming different fire management strategies that could have resulted in smaller or larger actual fires were developed based on expert judgment. These hypothetical scenarios allowed for a comparison of the air quality, specifically fine particulate matter ($PM_{2.5}$; particulate matter with a nominal mean aerodynamic diameter ≤2.5 µm) and ozone, and associated health impacts with the actual case study fires, as well as prescribed fires in each location, using U.S. EPA's Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE).

The case study analyses presented within this assessment demonstrate the importance of having refined information on prescribed fire activity to support air quality modeling of wildland fires. Within the area of each case study, air quality modeling indicates that the overall air quality impacts of wildland fires stem primarily from $PM_{2.5}$. Wildfires, such as the TC6 Fire, that occur in more remote locations and not near large population centers result in relatively small air quality and health impacts compared to larger fires, such as the Rough Fire. The estimated societal economic value of damages of illnesses and deaths attributed to smoke from each actual fire were:

- TC6 Fire: $18 million (M; 95% confidence intervals [CI]: $2 M to $47 M)
- Rough Fire: $3,000 M (95% CI: $260 M to $7,900 M)

The larger size of the Rough Fire and its closer proximity to population centers provided for a more meaningful comparison of the air quality and health impacts of different fire management strategies. Initial evidence indicates that a smaller wildfire adjacent to the Rough Fire that yielded positive resource benefits did not substantially reduce the overall fire perimeter of the Rough Fire, and thus minimally reduced the public health impacts. Addition of a prescribed fire targeted in a specific location to reduce fire spread, in combination with a wildfire that yielded resource benefits, could have dramatically reduced the overall size of the Rough Fire, resulting in an approximate 40% reduction in excess respiratory- and cardiovascular-related emergency department visits and hospital admissions, and premature deaths. The hypothetical scenarios for both case studies demonstrate that prescribed fires targeted for specific locations can have an effect on reducing the overall size of a wildfire. Although prescribed fires are timed for days with specific meteorological conditions to reduce population exposures to smoke, analyses show that air quality and public health impacts, while small, are still observed. The estimated societal economic value of damages of illnesses and deaths attributed to smoke from prescribed fires in each case study were:

- TC6 Fire Case Study: $4 M (95% CI: $0 to $9 M)
- Rough Fire Case Study: $60 M (95% CI: $5 M to $160 M)

Lastly, although not extensively examined within this assessment, preliminary analyses demonstrate that campaigns promoting actions and interventions to reduce or mitigate exposure to wildfire smoke can result in public health benefits, with potential reductions in population $PM_{2.5}$ exposures ranging from 15 to 30%.

It is important to recognize that the results of this assessment are limited to the geographic locations of the case study fires that have unique land management practices and resulting fire behavior that is specific to the ecosystems of each. In addition, although the results of this assessment demonstrate differences in the air quality and health impacts attributed to different fire management strategies, this analysis was unable to take into consideration key relationships between prescribed fire and wildfire that should be considered in future analyses. The analyses conducted within this assessment also treat prescribed fire activity as occurring at one point in time and does not take into consideration the temporal and spatial patterns of likely fire management strategies that include prescribed fire. Therefore, analyses do not consider how prescribed fires intersect with wildfire activity, including the probability of a wildfire occurring within the spatial domain of prescribed fires. As a result, the comparison of costs and benefits from smoke impacts between prescribed fires and hypothetical scenarios presented within this assessment is based on case studies where a wildfire occurred and does not take into consideration how the relationship between costs and benefits could differ in instances where wildfires have not yet occurred.

Overall, this assessment demonstrates the positive impact that interagency collaborations can have on complex issues at the intersection of land management and environmental public health, such as wildland fire. This initial assessment lays the foundation for future collaborative research and analyses by the partnering agencies to inform future land management and fire management strategies with the goal of reducing the air quality and health impacts attributed to wildland fire smoke.

# CHAPTER 1 INTRODUCTION

## 1.1 Background

The Wildland Fire Leadership Council (WFLC) was established in 2002 by "the Secretaries of Agriculture and the Interior to provide an intergovernmental committee [consisting of Federal, state, tribal, county, and municipal government officials] to support the implementation and coordination of Federal Fire Management Policy" (F&R, 2020b). The U.S. Department of Agriculture and the Department of the Interior (DOI) are official members and the cochairs of WFLC. One of the aims of WFLC is to improve communication and coordination with the public, specifically as it pertains to the understanding of the benefits and tradeoffs of prescribed fire versus wildfire.

At the request of WFLC, in January 2020, the U.S. Environmental Protection Agency (U.S. EPA) was asked to lead an assessment that would characterize and compare the impacts[1] of different fire management strategies, including prescribed fire. In this role, U.S. EPA would lead the development of *Comparative Assessment of the Impacts of Prescribed Fire Versus Wildfire (CAIF): A Case Study in the Western U.S.* in coordination with the U.S. Forest Service (USFS) and DOI, and with contributions from the National Institute of Standards and Technology (NIST). This report would provide a better understanding of the health and environmental impacts of wildland fire (i.e., prescribed fire and wildfire), specifically pertaining to smoke. The interagency approach being used to conduct this assessment is critical as USFS and DOI are experts in understanding various aspects of fire (e.g., fire management, fire planning, fire effects and ecology, incident response), NIST is an expert in the direct and indirect damages attributed to fire, and U.S. EPA provides expertise in understanding the public health and environmental impacts of fire, especially smoke. This collaborative effort has allowed for the leveraging of areas of expertise that are essential to characterizing complicated system-level impacts across the varying fire management strategies, and established the interagency linkages needed for future research activities.

## 1.2 Rationale

Fire has been used as a land management tool to return nutrients to the soil and remove detritus and excess fuels to reduce wildfire risk and effects, and to manage wildlife habitats and watersheds. Prior to modern land management, fire had been used for these same purposes and a myriad of other purposes

[1] Within this assessment, the term "impacts" refers to the main quantitative results, which includes the estimated air pollutant concentrations from the air quality modeling and the number of health events and associated economic values calculated using U.S. EPA's Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP–CE). The term "effects" is used to denote the other positive and negative consequences of wildland fire.

by Native Americans for millennia (Agee, 1993; Lewis, 1985, 1973). Over time our relationship with wildland fire, and the smoke that comes from these fires has become more complicated. A confluence of events have all contributed to increasing the likelihood of wildfire ignitions, including but not limited to, a history of fire suppression that has left a backlog of fuel; a changing climate with warmer temperatures; and humans moving at increasing rates into the line, area, or zone where structures and other human development meet or intermingle with undeveloped wildland or vegetative fuels, referred to as the wildland-urban interface [WUI; F&R (2020a)].

Over the past 30 years, on average approximately 5 million acres of wildlands in the U.S. have burned annually, with over 9 million acres burned in 2020 (Hoover and Hanson, 2021; NIFC, 2018). Although the number of fires has not changed significantly over this period, the size and intensity of the fires have increased as a result of higher temperatures, drought, earlier snowmelt due to climate change, and historically high fuel loading (e.g., undergrowth, tree density) Landis et al. (2017).

Although wildfire can be beneficial, it can also detrimentally impact ecosystems, damage animal habitats, decrease water quality and quantity, and in some instances create conditions leading to increased overland water flow and flooding. Additionally, with the rapid expansion of the WUI, wildfires are increasingly encroaching on American communities, posing threats to lives, critical infrastructure, and property (Lewis et al., 2018). The direct effects of fire itself are compounded by the equally significant effects of the smoke generated from fires, which can travel transcontinental distances and has been shown to have significant adverse effects on public health (U.S. EPA, 2019b). As the risk that wildfire poses to property and health has increased, especially when a wildfire is severe and catastrophic, the need to address this growing risk has also increased. At the same time, there is a need to recognize and maintain the ecological benefits of fire, which has always been a part of the natural landscape.

Various fire management strategies have been employed over time with the overall goal of reducing the potential for negative effects of wildfire, such as the overall size of a wildfire and the direct fire effects. These actions, which include prescribed fire and pile burns from thinning activities, have associated risks, specifically to air quality and corresponding health and environmental effects. Prescribed fire is perceived as lower risk compared to wildfire because the timing and area to be burned are managed to limit smoke impacts (i.e., dispersed both spatially and temporally). Prescribed fires are conducted when meteorological conditions are favorable, smoke production (fuel consumption) is less, atmospheric conditions support adequate smoke dispersion, and wind patterns allow smoke to move away from sensitive areas (e.g., populated areas, hospitals, schools, roadways). While prescribed fire is considered low risk, it is important to note that there is a risk continuum for wildfire that can change daily based on fire behavior resulting in a dynamic set of management actions. As a result, wildfire management can shift between full suppression efforts and, if conditions allow (e.g., wet fuel, anticipated precipitation), management that may achieve resource benefits. To date, limited information exists that allows for a direct, systematic, and comprehensive comparison of the air quality and associated health impacts of smoke from prescribed fire and wildfire. Together, prescribed fires and wildfire are how fire plays a role in the natural ecosystem. To ensure the effective use of prescribed fires to reduce the risk of catastrophic wildfire, decision makers need information on the air quality impacts associated with fire management strategies that include prescribed fires compared to strategies that do not.

Numerous research activities have focused on examining the nexus between fire, smoke, and ecological and health impacts. These activities have focused on this complex issue by examining how various conditions (e.g., fuel type, temperature, moisture) influence the subsequent emissions from a fire, how these emissions move over various geographic scales and topographies, the toxicologic and ecotoxicologic effects from smoke exposure, and population-level health impacts of smoke exposure. Recent studies have also evaluated actions and interventions that can be instituted to reduce the public health impacts during smoke episodes by melding together social science, behavioral science, and health risk communication. While all these activities have led to significant advancements in the science, the overall air quality impacts of different fire management strategies, which consist of different land management practices, including prescribed fire, are not well characterized. As a result, this complicates the decision-making process in determining the appropriate fire management strategy and land management action to implement at governmental levels ranging from local to federal.

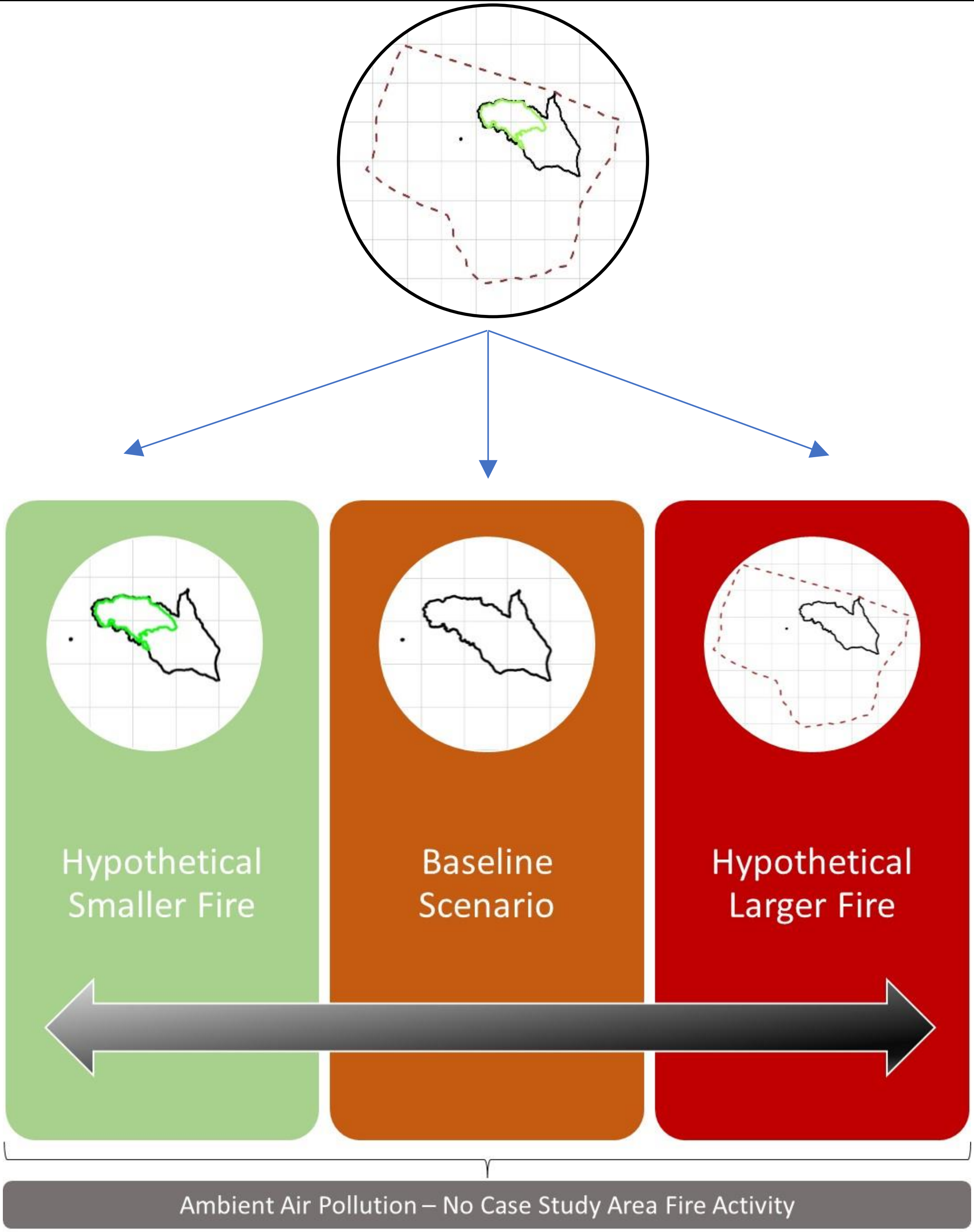
## 1.3 Novel Approach

The CAIF Report represents a unique opportunity to bring together experts spanning multiple disciplines related to fire science (e.g., air quality, monitoring, modeling, health effects, ecological effects) to conduct an integrated interagency assessment. The focus of this report consists of a novel modeling approach to estimate the air quality impacts, specifically of fine particulate matter (i.e., $PM_{2.5}$ [particulate matter with a nominal mean aerodynamic diameter $\leq 2.5$ µm]) and ozone, in response to different fire management strategies, and the associated health and economic impacts. To conduct such an analysis, this report will focus on two case study fires, both of which occurred in the Western U.S.: (1) Timber Crater 6 (TC6) Fire that occurred from July 21−26, 2018 in Oregon; and (2) Rough Fire that occurred from July 31−October 1, 2015, in California. These fires were selected, in part, because they represented interagency fires managed by both USFS and DOI, and both had data available, to varying degree, on previous land management practices. Due to the difference in the scale of these two fires, the TC6 Fire burning approximately 3,000 acres and the Rough Fire burning approximately 150,000 acres, and the different land management and fire management strategies employed in both locations there will be slight differences in the resolution of the analyses and the analytical approaches between the fires.

The modeling component of the analysis, which is the main focus of this report, will estimate $PM_{2.5}$ and ozone concentrations for the actual fire and compare those air quality impacts to hypothetical scenarios based on different fire management strategies resulting in smaller or larger fires for each of the case studies, as depicted in Figure 1-1. In addition to the hypothetical smaller and larger fires, analyses also examine prescribed fire activity, and in the case of the Rough Fire, the perimeter included the footprint of a recent wildfire that burned at lower intensity and yielded positive resource benefits. For both case studies, the prescribed fire analyses do not account for the episodic nature of prescribed fires that are conducted over years to decades to keep fuel loads at a level needed for fire suppression opportunities. For the TC6 Fire case study this resulted in the multiple prescribed fires that occurred over many years in the vicinity of the TC6 Fire to be modeled as individual events within the same month when prescribed fire activity was known to have occurred. This is in contrast to the Rough Fire case study where the focus was on the modeling of a single prescribed fire event that was planned but did not occur. Prescribed fire activity was treated this way within this assessment for numerous reasons including current limitations in the ability to account for the timing of retrospective prescribed fire activity and sparseness of available data. Further, the prescribed fires examined within these case studies are not intended to account for the entirety of a spatial area needed to prevent the spread of a larger wildfire in both areas.

For both the TC6 and Rough Fire analyses, to facilitate comparison of impacts across the different fires being examined within the case study areas, the region-wide air quality impacts (i.e., $PM_{2.5}$ and ozone) will be compared to a baseline of ambient air pollution with no case study area fire. This approach allows for an estimation of the burden associated with each of the case study fires and a direct comparison of the health impacts and associated economic values, across each fire and hypothetical scenario using U.S. EPA's Environmental Benefits Mapping and Analysis Program—Community Edition [BenMAP–CE; U.S. EPA (2019a)].

For the TC6 Fire the hypothetical scenarios developed consist of: (1) a smaller hypothetical TC6 Fire in a heavily managed area (e.g., most prescribed fire activity), which would equate to a wildfire with less fuel, a smaller fire perimeter, and less daily emissions; (2a) a larger hypothetical TC6 Fire, but not the "worst-case" scenario, due to no land management which would equate to a wildfire with more fuel, a larger fire perimeter, and more daily emissions; and (2b) a much larger, hypothetical "worst-case" scenario TC6 Fire with no land management (i.e., no prescribed fire) which would equate to a wildfire with the most fuel, largest fire perimeter, and largest daily emissions (Figure 1-2). In addition to each of these scenarios, analyses will also include an examination of only the prescribed fires that occurred around the TC6 Fire, for a comparison of air quality and health impacts between prescribed fires and the actual wildfire. These prescribed fires were selected based on actual historical prescribed fire activity in this area as a preliminary comparison point to the TC6 Fire and hypothetical scenarios.




Note: Black outline = actual fire perimeter, green outline = hypothetical smaller fire perimeter; dotted purple outline = hypothetical larger fire perimeter.

**Figure 1-1 Overall approach to comparing fire management strategies in case study analyses.**

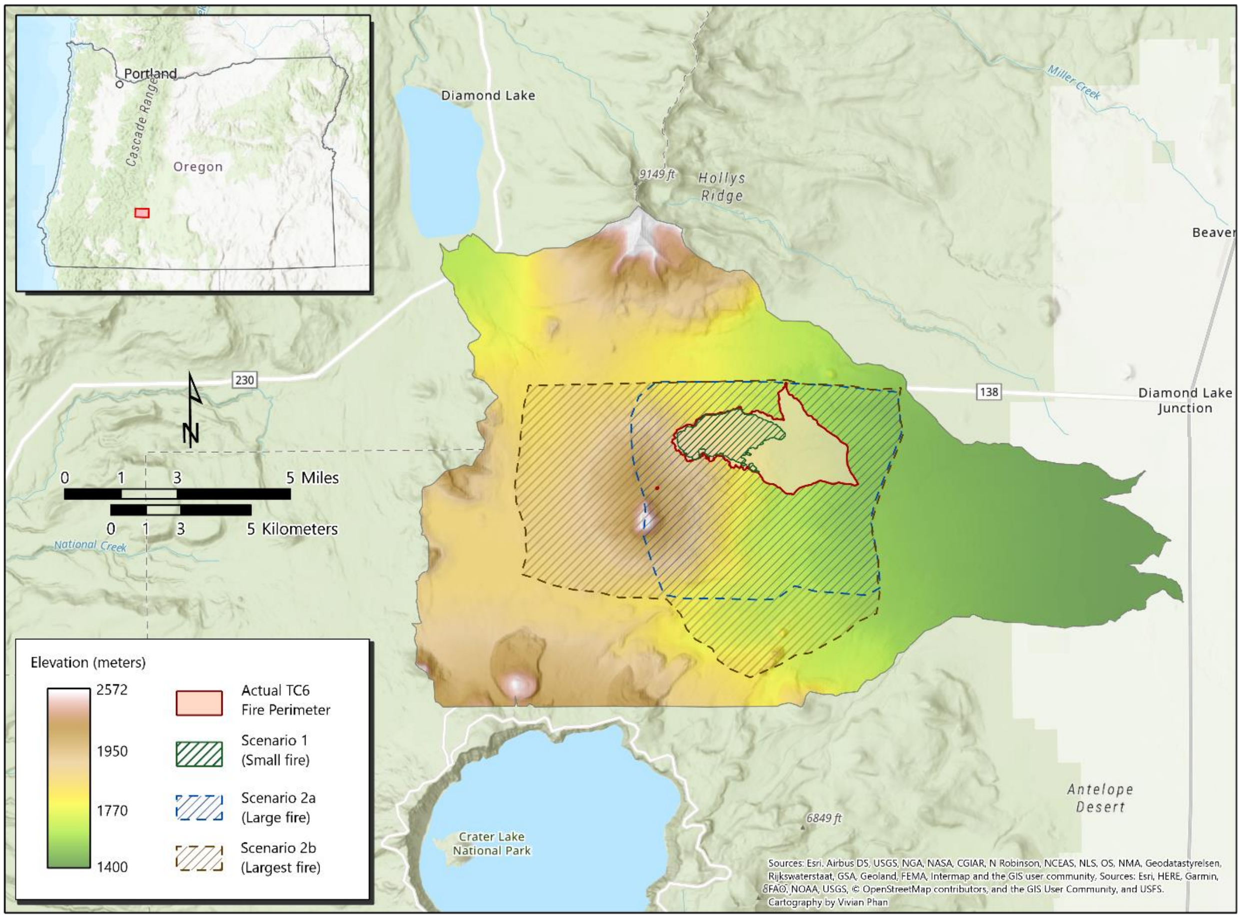



**Figure 1-2 Map of fire perimeters of hypothetical scenarios and actual fire for the Timber Crater 6 (TC6) Fire case study.**

The Rough Fire was selected for the second case study because its larger size and location provides an opportunity to assess impacts on a larger downwind population and evaluate differences in both air quality and health impacts for different hypothetical fire management strategies versus the TC6 Fire. For the Rough Fire, analyses will encompass the actual fire, which occurred over approximately 2 months, and the impact of multiple hypothetical scenarios, representing different land management practices, on both the spread of the Rough Fire and corresponding air quality impacts. In comparing air quality impacts between the actual Rough Fire and the hypothetical scenarios, the entire 2 months that encompassed the Rough Fire will be modeled with the air quality impacts diverging at the point where the Rough Fire would have reached the perimeters of two fires considered within this case study, the Boulder Creek Prescribed Fire and the Sheep Complex Fire. Within the Rough Fire area there was no previous prescribed fire activity, as a result, this case study models the proposed Boulder Creek Prescribed Fire, which was a prescribed fire that USFS had planned, but did not occur; and the Sheep Complex Fire, which is a wildfire that occurred in 2010 due to a lightning strike and as a result of wet fuel conditions resulted in resource benefits. Hypothetical Scenario 1, also referred to as the smaller hypothetical Rough Fire, revolves around examining the combined impact of a prescribed fire and wildfire that resulted in resource benefits (i.e., reduced fuels) on reducing the spread and air quality impacts of the Rough Fire. Hypothetical Scenario 2, also referred to as the larger hypothetical Rough Fire, will allow for the fire perimeter of the Rough Fire to progress into the area of the Sheep Complex Fire as if both the Boulder Creek Prescribed Fire and Sheep Complex Fire did not occur. In addition to comparing each hypothetical scenario to the actual Rough Fire, air quality and health impacts will also be compared individually to the Boulder Creek Prescribed Fire and the Sheep Complex Fire. Figure 1-3, depicts the fire perimeters that are examined in the Rough Fire case study.

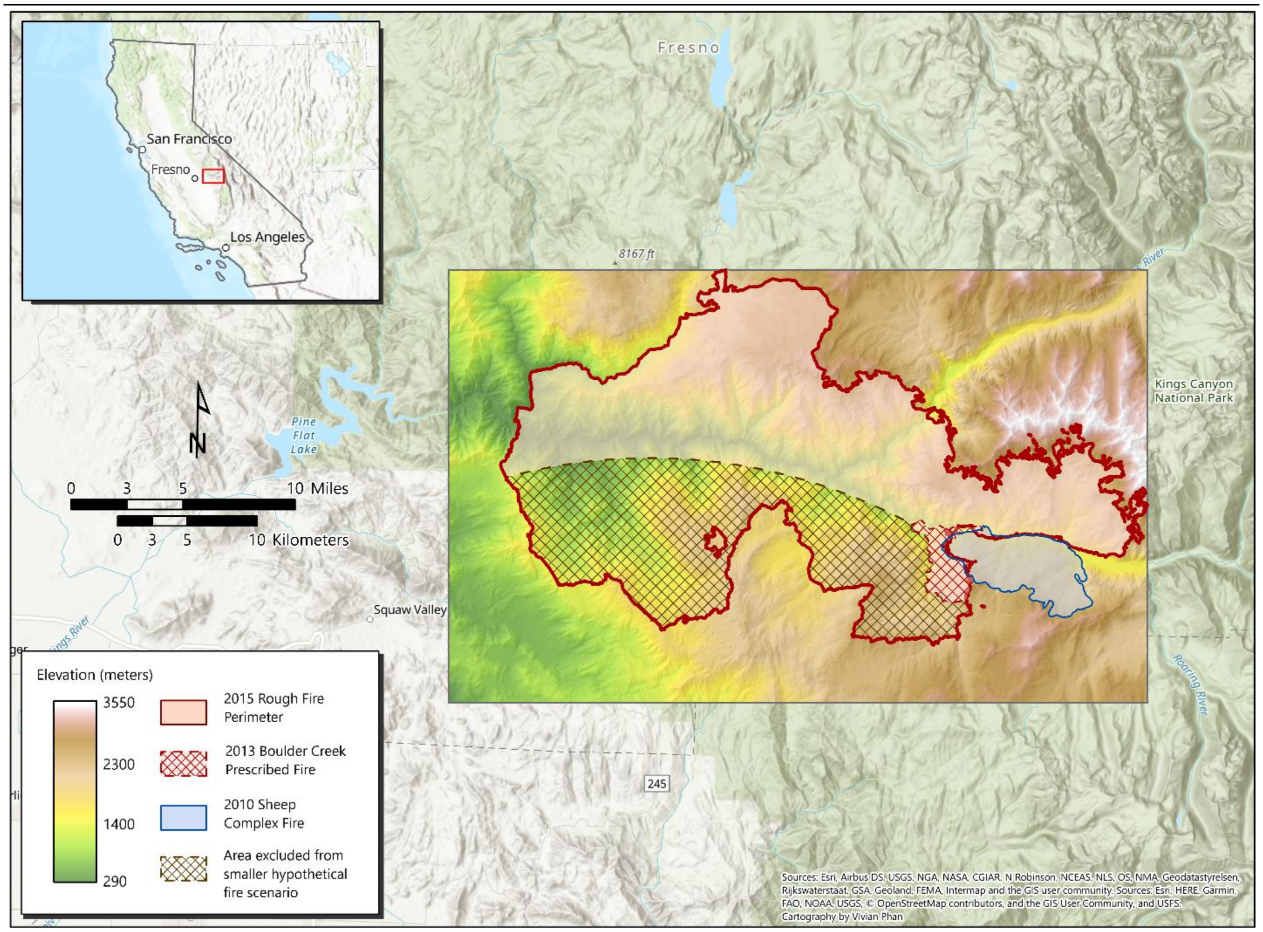



**Figure 1-3 Map of fire perimeters for the Rough Fire case study.**

While the direct comparison of the air quality impacts of different fire management strategies can inform the benefits and tradeoffs of each, it is also important to recognize that specific actions or interventions could also be taken to minimize public health impacts. However, the likelihood of individuals taking precautionary measures to reduce smoke exposure can vary between wildfire and prescribed fire events depending on the presence and effectiveness of public health messaging as well as the amount of lead time available for messaging to inform the public and the public's ability to act on that messaging. As a result, it is important to also consider the potential public health implications of actions or interventions that could be employed to reduce population exposure to smoke when evaluating tradeoffs between wildfire and prescribed fire. Therefore, a crude estimation of the potential public health benefits that could be realized in each case study analysis was conducted for different actions meant to reduce or mitigate smoke exposure. For the actual TC6 and Rough Fires, the deployment of Air Resource Advisors (ARAs) by the USFS, in combination with the respective state and local air quality agencies, efforts are taken to predict smoke impacts, and warn the public of the hazards of smoke and the benefit of minimizing exposure. The examination of smoke exposure reduction actions within this assessment does not reflect a formal analysis of post-fire effectiveness of public health messaging for either the TC6 or Rough Fires.

Although the comparison of air quality impacts and associated health and economic impacts between the different fire management strategies represents the main output of the CAIF Report, in order to put the results in the proper context, the report also captures qualitatively, and in some cases quantitatively, other factors that can influence a full accounting of the benefits and damages associated with each fire management strategy. This includes information pertaining to baseline forest conditions, air quality monitoring of fires, direct fire effects on health, damages due to fire and smoke, and ecosystem benefits and damages.

## 1.4 Goals of This Report

The goal of the CAIF Report is to provide an initial quantitative assessment of the air quality and associated health, and economic impacts attributed to different fire management strategies, including prescribed fire, through an extensive modeling exercise. This quantitative assessment will be supplemented with qualitative discussions to highlight the current state of the science that informs this assessment, and identify deficiencies that if addressed, can further inform analyses of fire management strategies. The collective assessment within this report of the benefits and damages associated with both fire and smoke can contribute to a fuller characterization of the benefits and tradeoffs of different fire management strategies.

This report represents an initial step in the process of conducting assessments to characterize the impacts of different fire management strategies to inform both public health actions to reduce population exposures to wildfire smoke, and future land management decisions. By attempting to more fully account for the impacts of different fire management strategies, tradeoffs can be assessed to ensure the appropriate land management actions are taken to maintain forest health and minimize the public health impacts attributed to wildland fire smoke.

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# CHAPTER 2 CONCEPTUAL FRAMEWORK FOR EVALUATING AND COMPARING DIFFERENT FIRE MANAGEMENT STRATEGIES

## 2.1 Introduction

Fire is an important element of the natural landscape and is highly influenced by both natural and anthropogenic factors. Fire management decisions are made at multiple governance levels to influence the types of fires that affect different vegetative systems. Goals include increasing overall forest and rangeland health and resilience and reducing the potential for the occurrence of uncontrolled and often catastrophic wildfire. Current federal fire policy recognizes the importance of wildland fire (i.e., prescribed fire and wildfire) "as an essential ecological process and natural change agent that will be incorporated into the (land management) planning process [which includes the development of] Fire Management Plans (FMPs), programs, and activities support[ing] Land and Resource Management Plans and their implementation" (Interagency Federal Wildland Fire Policy Review Working Group, 2001). Different fire management strategies before, during, and after a fire can result in different effects on the landscape and adjacent communities, including the smoke that results from wildland fire. Understanding the effects of different fire management strategies, defined as a planned set of activities to achieve resource objectives, can help fire managers make informed decisions that reduce adverse effects, both directly from the fire itself as well as from the smoke it produces, while yielding desired ecological and risk management benefits. In this chapter, we describe a conceptual framework for evaluating and comparing different fire management strategies, using a range of metrics to characterize and quantify effects.[2] Fire management strategies are developed to achieve multiple objectives, including promotion of ecological benefits, protection of lives and property, safe and effective responses that minimize risks to firefighting personnel, and reduction in likelihood of severe and catastrophic wildfire. While the focus of this assessment is on the quantification of the air quality and associated health impacts attributed to smoke exposure, it is also important to recognize the broader effects (including both positive and negative effects) of wildland fire in the process of considering different fire management strategies. Therefore, subsequent chapters provide more in-depth discussions of the elements of this framework and its implementation in comparing the effects of different fire management strategies.

[2] Within this assessment, the term "impacts" refers to the main quantitative results, which includes the estimated air pollutant concentrations from the air quality modeling and the number of health events and associated economic values calculated using U.S. Environmental Protection Agency's (EPA's) Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP—CE). The term "effects" is used to denote the other positive and negative consequences of wildland fire.

The overarching question that guides the evaluation conducted within this framework is What are the expected effects (both positive and negative) of alternative fire management strategies over both short (during the event) and long term (post-event) time horizons? with an emphasis within this assessment on the smoke impacts. Critical to this question are the ideas of expected positive and negative effects, a recognition that fire needs to be viewed over a management-relevant temporal and spatial frame, and that fire is inevitable and necessary. While some effects can be quantified and monetized broadly (i.e., nationally), and thus used in a more traditional cost-benefit comparison, it is important to recognize that this can be challenging when examining the effects of individual fires. Many of the effects of wildland fire are not easily quantified or assigned a dollar value. As a result, while this assessment estimates the air quality and the dollar value of health impacts of smoke for quantitative comparisons, it also provides additional qualitative discussions of other effects (i.e., positive and negative) of both direct fire and smoke.

## 2.2 Expected Value Framework

An expected value (EV) framework is used within this assessment because of the inherent stochastic nature of fire in the landscape. While in many cases, a wildfire is likely to occur given a sufficient time horizon, both the timing and location of a wildfire event is uncertain as compared to prescribed fires which are planned events that occur at specific times of the year and in specific locations. Wildfires can also reburn the same area with very different outcomes because of the reduction or increase in fuel loads. For example, many of the prescribed fires in the southeastern U.S. are maintenance burns designed to keep fuel loads low and occur on a fairly frequent basis. A range of periodicity between wildfires had been established for different ecosystems; however, under a changing climate, the previous assumptions on potential risk of wildfires are often challenged. The management of wildland fire can result in a desired outcome (positive effect) or an undesirable outcome (negative effect). Fire management strategies such as prescribed fires can reduce the uncertainty in outcomes from fires. When comparing strategies, both stochastic and nonstochastic elements need to be expressed in a way that allows for equivalent comparison. In a typical cost-benefit framework, comparisons between alternatives requires a complete accounting for all costs and benefits, both direct and indirect. The conceptual framework used in this assessment aims to provide a full accounting of the overall effects of wildland fire; however, the ability to quantify all elements is limited. As such, this chapter emphasizes the elements that will form the basis of and be incorporated into the main component of this assessment, the quantitative comparison of the smoke impacts of wildland fire. Key details of the inputs in this comparative analysis are the air quality modeling and health impact analyses described in CHAPTER 5 and CHAPTER 8, respectively. This focus on smoke impacts is to address a key gap in the overall knowledge base regarding wildland fire management, however, this is not intended to suggest that the other positive and negative effects of wildland fires and fire management strategies are less important. A full accounting of costs and benefits of those strategies will require further development of models and methods to quantify effects across the full range of domains, including ecological, health, safety, prevention, and risk to highly valued resources and assets.

The expected value of a specific fire management strategy requires knowledge of (1) the impacts effects associated with different fire types (e.g., prescribed fire vs. wildfire), (2) the effects associated with different management techniques (e.g., targeted thinning, prescribed fires), and (3) probabilities of these effects. Two other key concepts are fire ignition probabilities and the management of a wildfire once it has ignited. Ignition probabilities, a key factor in determining risk from wildfires, indicate the chance that a wildfire will occur over a specified time period within a defined spatial domain (Hunter and Robles, 2020). In managing wildfire risk, land managers utilize an operational risk framework that gives primary consideration to public and firefighter safety. This risk framework is intended to consider the degree to which the extent, intensity (energy output), and severity (effects on ecosystems) of a wildfire can be mitigated once started based on the land management plans, fire history fuel, and weather conditions. Both ignition probability and management can be positively or negatively impacted by the fire management strategy.

Within this report, costs of management strategies are defined as the specific economic expenditures associated with implementing specific management actions. For example, the costs associated with a management strategy that includes mechanical thinning would include but not be limited to the costs of equipment and labor costs for equipment operators. Costs here do not refer to the outcomes of management actions, but instead these outcomes are referred to as effects, which can be either positive or negative (see Table 2-1). One consequence of a fire management strategy may be reductions in future costs of fire management.

For this conceptual framework, the expected value ($EV_i$) of effects (positive + negative) for a fire management strategy $M_i$ is specified as:

$$EV_i = PF_i + NF_i + P(\text{WF ignition}|M_i) \times (F|M_i)$$

**Equation 2-1**

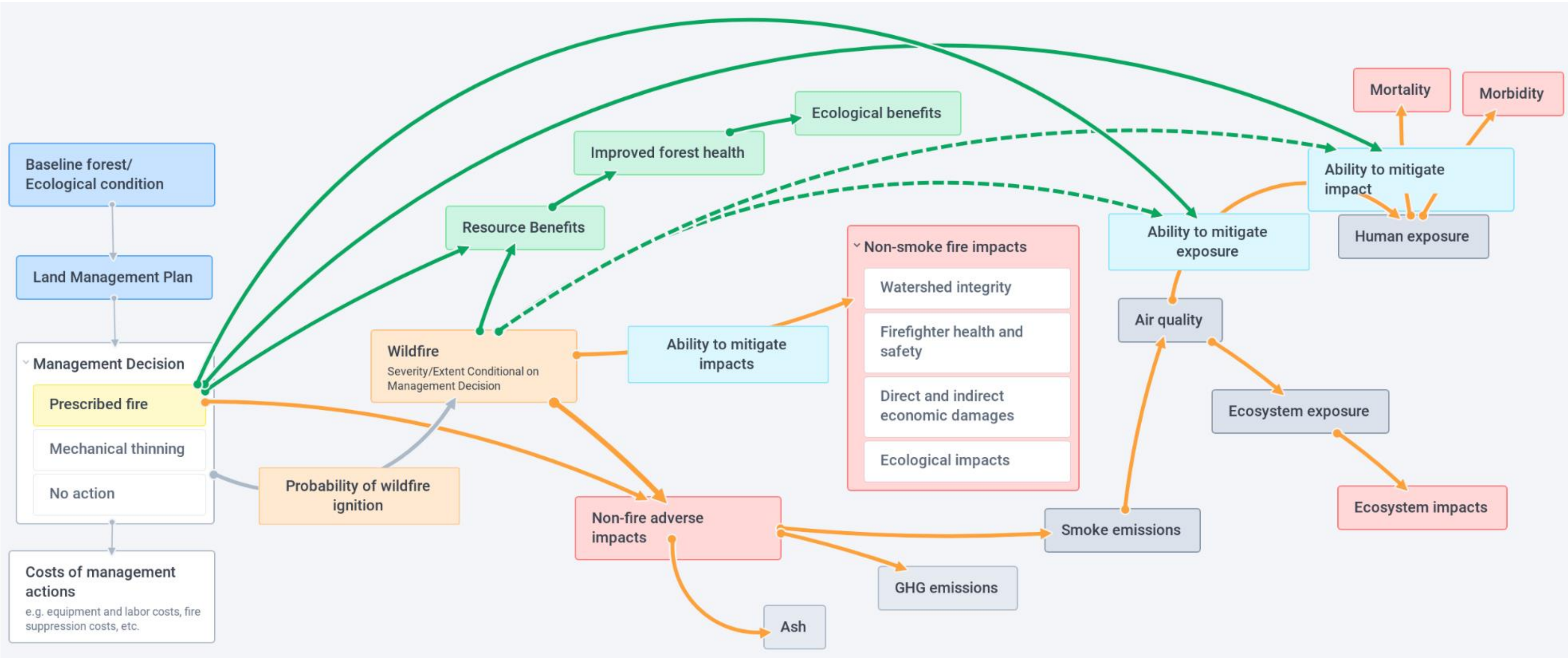
Where $PF_i$ are prescribed fire-related effects conditional on $M_i$, $NF_i$ are nonfire effects from $M_i$, $P$(WF ignition|$M_i$) is the probability of wildfire ignition conditional on $M_i$, and $F|M_i$ are fire-related effects conditional on $M_i$ and land management objectives once a fire is ignited. Effects include all of the positive and negative effects associated with a fire management action. In most applications, *EV* will be expressed in dollars for comparison with the dollar costs of the management strategy, and because dollars are a unit in which all damages can be theoretically expressed. Essentially, the expected value is the effect of the fire management action itself plus the ignition-probability-weighted effects of wildfire conditional on the management strategy. For fire management strategies that do not include prescribed fire, the first term will be zero.[3]

The net benefit of a fire management strategy is defined as $EV_i - C_i$, where $C_i$ is the cost of management strategy $M_i$. Within this assessment, fire management costs are treated as a known quantity. There is likely to be uncertainty in those fire management costs as well; however, addressing this uncertainty is beyond the scope of the assessment.

## 2.3 Components of the Conceptual Framework

A graphical representation of the conceptual framework is presented in Figure 2-1. This figure is meant to serve as an anchor for discussions of elements of the framework. The following discussions of each element provide a short description and references to the chapters and sections of this report that provide more detailed qualitative discussions, and where possible, quantification methods and modeling results.

[3] There may be some nonsmoke or fire-related benefits and damages associated with other fire management approaches such as mechanical thinning. We are not quantifying those impacts for this assessment.




GHG = greenhouse gas.

In the figure, forest management inputs are colored dark blue, management decisions and their nonsmoke related effects are colored white, resource benefits are colored green, mitigation actions are colored light blue, fires are colored yellow and orange, fire damages are colored red, and smoke exposure related elements are colored gray. The green arrows indicate positive effects, and the orange arrows indicate negative effects. Dotted lines represent linkages that may occur but are less certain that solid lines.

**Figure 2-1 Conceptual framework for evaluating and comparing fire management strategies.**

### 2.3.1 Baseline Wildland Fuels Vegetation and Resource Management Conditions

Baseline vegetation conditions, which are discussed in detail in CHAPTER 3, influence the probability of a wildfire occurring and the intensity and characteristics of a wildfire, including smoke generation. These wildland fuels vegetation conditions include location, size, density, stand composition, ladder fuels[4], height to live crown, understory condition, and surface fuel loads. Other vegetation and resource management attributes included in land management plans (see CHAPTER 3) or that influence the management and outcomes of a fire include distance from the wildland to populated areas (e.g., location in or relative to the wildland–urban interface [WUI]); proximity to Superfund sites, mining sites, and other legacy contaminant sites; distance to watersheds that provide community drinking water, plant and wildlife habitats, infrastructure, and consideration of positive impacts from fire (e.g., restoring ecosystems, fuels reduction).

### 2.3.2 Types of Fires

There are two types of wildland fire, as designated in statute 40 CFR § 50.1—Definitions (U.S. EPA, 2020a), and by policy, as stated in National Wildfire Coordinating Group (NWCG) Glossary of Wildland Fire (NWCG, 2021). The following two definitions will be used throughout this assessment in order to remain consistent with their use in air quality regulation and in Federal wildland fire management policy.

- Prescribed fire: Also referred to as planned fires, controlled burns, or prescribed burns, 40 CFR § 50.1(m) defines a prescribed fire as "any fire intentionally ignited by management actions in accordance with applicable laws, policies, and regulations to meet specific land or resource management objectives" (U.S. EPA, 2020b).
- Wildfire (natural and human caused): 40 CFR § 50.1(n) defines a wildfire as "…any fire started by an unplanned ignition caused by lightning; volcanoes; other acts of nature; unauthorized activity; or accidental, human-caused actions, or a prescribed fire that has developed into a wildfire. A wildfire that predominantly occurs on wildland is a natural event" (U.S. EPA, 2020c).

Effects are expected to vary based on characteristics such as types of biomass burned, burn conditions (e.g., temperature, humidity, wind), season, duration, intensity, and location relative to populated areas (which can vary from minute to minute, day to day, and site to site) within each area burned. Fires also vary based on the history of previous fire occurrences, the periodicity and intensity of previous occurrences, and the management and land use history of the area in question. For the purposes of this conceptual framework, the focus is on two different types of fires (i.e., prescribed fire and

[4] Fuel that allows fires in low-growing vegetation to jump to taller vegetation.

wildfire), recognizing that within each category, there will be a high degree of variability based on these characteristics.

Although rare, prescribed fires can be declared a wildfire when they are no longer meeting objectives (e.g., escaping boundaries, intensity, smoke management). A 2013 report from the Wildland Fire Lessons Learned Center (LLC reported that in 2012, only 0.08% of prescribed fires escaped their planned boundaries (LLC, 2013). This includes all escapes on federal, state, tribal, and private lands that were reported into the Wildland Fire LCC Incident Review Database, along with additional agency notifications and media reports that were available.

Wildfires vary widely in their effects depending on location, meteorological conditions during the fire, and the types of forests where they occur. A wildfire may be also be deemed "catastrophic" (Wooten), resulting in severe economic, social, and ecological effects (Carey and Schumann, 2003), including a high percentage of dead trees (Wooten). While there is a great deal of year-to-year variability, in recent decades, wildfires have affected an increasing number of acres, with an average of 6.9 million acres burned from 2000−2019 compared with an average of 3.2 million acres burned from 1980−1999 (NICC, 2019).

On February 13, 2009, the Guidance for Implementation of Federal Wildland Fire Management Policy was issued (FEC, 2009). This guidance provides for consistent implementation of the 1995 Federal Fire Policy and the 2001 update. By policy, management response to a wildfire on federal land is based on objectives established in an applicable Land/Resource Management Plan (L/RMP) and or FMP. Fire management objectives are affected by changes in fuels, weather, topography, varying social and political understanding and involvement of other governmental jurisdictions that may have different missions and objectives. Managers use a decision support process to guide and document wildfire management decisions. The process includes land management objectives, situational awareness, analysis of hazards and risk, defining of implementation actions and the fire management decision documentation and rationale.

A full range of fire management strategies can be used to achieve L/RMP and FMP objectives. Wildfire may be managed solely to meet protection objectives, such as protecting values at risk of loss by suppressing the fire in the safest, most effective, and efficient way. The initial response may be as simple as evaluating the location of the fire without further on-the-ground active suppression action in areas where the fire is distant from valued assets that require action to protect or where the risks from exposure for firefighters is higher than the value of the assets that would be protected. Wildfire may be managed concurrently for one or more objectives, and the objectives can change as the fire spreads across the landscape. For example, a wildfire can be managed for suppression to protect points of valued resources while at the same time taking no action when or where resource values are being enhanced.

No matter how a wildfire is being managed, firefighter and public safety is the first priority. All fire management activities and decisions must reflect this commitment. A fuller description of how wildfire can be used as a land management tool can be found in CHAPTER 3.

### 2.3.3 Fire Management Strategies

Severity of fires is determined by a number of factors, some of which can be affected by management practices (e.g., forest structure, fuels, vegetation composition) and others which cannot be controlled (e.g., weather, location). Most fire management strategies focus on fuel load reduction, which is a management strategy that involves "manipulation, including combustion, or removal of fuels to reduce the likelihood of ignition and/or to lessen potential damage and resistance to control" (USFS, 2003a). Fuel reduction strategies aim to reduce the probability of ignition and reduce the intensity and uncontrolled spread of wildfires (Agee and Skinner, 2005). Thus, fuel reduction strategies directly affect two key parameters in the framework, *P*(WF Ignition) and *P*(control). Two common practices for fuel load reduction include prescribed fires and mechanical thinning.

#### 2.3.3.1 Prescribed Fires

Prescribed fires, as defined in Section 2.3.2, are a fire management tool that uses planned, controlled fires to reduce fuel loads and achieve the ecological benefits of fires while reducing the potential for catastrophic uncontrolled fires. There is growing evidence that prescribed fires can reduce surface fuels and reduce fire severity while maintaining or improving forest health (Hunter and Robles, 2020; Kalies and Kent, 2016; USFS, 2003b).

Prescriptions for fire are based on clearly defined objectives, which might include ecological aspects such as habitat diversity and endangered species recovery, as well as fuel reduction to reduce the potential of high intensity, high severity fires. Prescriptions also take into account environmental and meteorological conditions, fuels, burn area, and planned approaches for suppression once objectives are met to reduce potential adverse impacts, including those associated with smoke emissions (USFS, 2021; U.S. EPA, 2020d). The effectiveness of prescribed fires in reducing the potential for severe fires is dependent on weather patterns and ecosystem characteristics such as types of fuels, as well as the interactions between them [e.g., drought may affect fuel moisture content; Fernandes and Botelho (2003)].

On federal and most state lands, prescribed fire is only used after thorough preplanning and only by highly trained and experienced professionals. It is only implemented when conditions meet preplanned elements and adequate contingencies are in place or confirmed by managers and Agency Administrators. Go/no-go checklists are used to determine compliance with policies and the prescribed fire plan parameters (NWCG, 2017).

#### 2.3.3.2 Mechanical Fuel Reduction

Mechanical treatments to thin trees and remove fuels can be used in conjunction with prescribed fires or be employed in places and times when prescribed fires cannot be used (McIver et al., 2013). They require equipment as well as plans for disposal or utilization of significant quantities of small trees (Agee and Skinner, 2005; Rummer et al., 2003). Thinning trees can reduce surface fuel loads, and also reduce risks of crown fires (fires that spread across tree canopies) which can cause severe damage. There are multiple types of thinning that affect different aspects of forest composition, including low thinning that removes small trees, crown thinning which removes medium size trees, and selection thinning, which removes larger, more marketable trees (Agee and Skinner, 2005). How the residual wood from the thinning operations is disposed of can have a substantial impact on surface fuel availability with chipping or burning of the unusable tops of trees having the greatest impact on reducing fuel loads.

There is limited observational data on the degree to which mechanical thinning, alone or in conjunction with prescribed fires changes the probability of ignition or intensity and severity of fires. Simulations have shown that removing small trees and "ladder fuels" (i.e., fuels that allow fires to climb up to forest canopies) can be effective in reducing fire severity, especially when in conjunction with prescribed fires (Agee and Skinner, 2005).

#### 2.3.3.3 Fuel Treatment Effectiveness

In 2006, the U.S. Department of Agriculture Forest Service and Department of the Interior (DOI) Bureau of Land Management (BLM) initiated a program to evaluate the effectiveness of hazardous fuel treatments (prescribed fire and mechanical) designed to reduce the potential of high intensity, high severity wildfires. When a fuel treatment is tested by wildfire, an evaluation is performed to determine the effectiveness of the treatment in changing the fire behavior (e.g., going from a crown fire to a surface fire) and/or helping manage the wildfire. In 2011, the Forest Service and the DOI land management agencies (Bureau of Indian Affairs, BLM, Fish and Wildlife Service, and National Park Service) made the effectiveness assessment mandatory whenever a wildfire impacted a previously treated area.

Since 2006, almost 14,860 assessments have been completed (IFTDSS, 2021). About 89% of the fuel treatments were effective in changing fire behavior or helping with management of the wildfire or both (IFTDSS, 2021). In addition, prescribed fire treatments were observed to be the most effective in changing fire behavior and reducing overstory mortality from wildfires. Unfortunately, until recently, due to limitations in reporting systems the ability to detect all wildfire fuel treatment interactions has been limited, resulting in a significant under sampling of fuel treatment effectiveness monitoring, mostly on the smaller fires (less than 1,000 acres).

## 2.3.4 Effects of Fire

Prescribed fires and wildfires have the potential for both positive and negative effects, although the magnitude of potential effects differs. The goal of prescribed fires is to reduce the fuel loads that will result in decreasing the frequency, intensity, and severity of a wildfire while providing for safe and effective response to wildfire and protecting highly valued resources and assets. In general, positive effects that occur directly from fire result from improvements in landscape/watershed health which yield ecological benefits or ecosystem services. Negative effects occur both directly, as a result of the fire itself, or indirectly, through emissions of smoke and ash. The magnitude, scale, and duration of these effects will depend highly on the type of fire, the fuel conditions, the terrain, and the fire weather conditions, as well as the location relative to the WUI, and downwind populations. Air quality impacts result from smoke emissions that impact ambient concentrations of numerous pollutants including ozone and particulate matter, specifically fine particulate matter ($PM_{2.5}$ [particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm]; see CHAPTER 4 and CHAPTER 5), which have been shown to contribute to a wide variety of adverse health and ecological impacts [see CHAPTER 6; Holm et al. (2021); Jaffe et al. (2020); Cascio (2018)]. The severe wildfires occurring in the western U.S. over the past few years causing loss of life and property and the reversal of trends in air quality improvements in the western states attributed to increasing wildfire emissions (McClure and Jaffe, 2018) have drawn the attention of the National Academies of Science, Medicine and Engineering (NASEM, 2020) and other medical professional organizations (Kaufman et al., 2020; Rajagopalan et al., 2020; Rice et al., In Press) which are strongly advocating for attention to finding solutions to prevent such severe wildfires while simultaneously mitigating the adverse effect of exposure to smoke.

### 2.3.4.1 Direct Fire Effects

#### 2.3.4.1.1 Benefits to Wildland Ecosystems

Many wildland ecosystems have adapted to periodic fires. In fact, a number of tree species such as pines depend on fire for reproduction, as do many shrubs and most grasses. Other species, such as Sequoias, rely on periodic fires to open up forest canopies to allow saplings to grow and flourish. Open canopies also support the growth of shade-intolerant plants and reduce the probability of crown fire. Fires also convert brush and dead trees and plants to nutrient rich ash which can be beneficial to established trees and provide essential nutrients for new forest growth. These nutrients are also important to support soil microbes which increases the overall health of wildland ecosystems. Fires and smoke can also remove invasive species not adapted to fires, as well as reduce populations of destructive insects and diseases (Neary et al., 2005; Brown and Smith, 2000; Smith, 2000). In some cases, for example cheatgrass, fires can also help to control invasive species (Neary et al., 2005; Brown and Smith, 2000;

Smith, 2000; Young et al., 1987). Detailed information on benefits of wildland fire on wildland ecosystems is provided in CHAPTER 3.

#### 2.3.4.1.2 Benefits to Fire Management (Post-Event)

As discussed in Section 2.3.3.1 and Section 2.3.3.3, prescribed fires are designed to reduce the potential for severe fire damages by changing the behavior of a subsequent wildfire and making it easier to manage. This can result in fewer risks to firefighting personnel during subsequent wildfires, as well as reducing economic damages, ecological damages, and health impacts to populations from fires and poor air quality caused by smoke.

#### 2.3.4.1.3 Fire Damages

Direct fire damages, described in CHAPTER 7, include effects to firefighters (including impacts from direct smoke inhalation), effects to populations in the vicinity of fires, economic damages, and ecological damages. Health impacts to firefighters can be immediate, due to extreme heat, burns, asphyxiation, overexertion, or accidents, or can be delayed, due to smoke-related diseases such as cancers and chronic conditions such as heart disease that may be associated with prolonged and repeated exposures to extreme heat, overexertion, and stress (Domitrovich et al., 2017). Effects to populations in the vicinity of fires include deaths, injuries, and psychological damages (Thomas et al., 2017). Economic damages include the value of lost property; loss of marketable timber; direct and indirect costs of evacuations, including business interruption; damages to infrastructure, such as downed power lines or damaged roadways; and the value of lost recreational resources, due to either safety-related closures or fire damage (Thomas et al., 2017). Ecological damages can occur due to changes in vegetation composition; conversion from one vegetation type (e.g., forest) to another (e.g., shrubs); damage to soils, which could lead to flooding and degraded water quality and quantity; loss of habitat and endangered or threatened species; increased susceptibility to insects and diseases; and climate-related damages resulting from releases of greenhouse gases (GHGs) and loss of carbon sequestration potential (Thomas et al., 2017).

### 2.3.4.2 Effects from Smoke and Ash

All wildland fires produce smoke and ash. The amount and composition of smoke can vary between the types of fires due to the types of burn conditions and type, loading, and consumption of fuels. Release height and transport of smoke can also vary between types of fires (as well as within types of fires) depending on meteorological conditions and burn conditions. For example, plume rise will depend on the temperature of the fire, and long-range transport of smoke will depend on wind speed and direction, as well as plume rise. The impacts associated with smoke emissions will depend on the emissions density, how far and in which direction the smoke travels, and on the proximity of a fire to downwind populated areas. CHAPTER 4 and CHAPTER 5 describe approaches used to monitor and model air quality impacts from wildland fire smoke.

##### 2.3.4.2.1 Smoke-Related Effects

Smoke has immediate impacts directly in the vicinity of a fire, as well as impacts downwind of a fire due to worsened air quality. There are smoke transport mechanisms which function under flaming and smoldering phases of a fire. These phases are important in terms of emissions, how far the emissions will transport and implication in terms of safety impacts such as roadway visibility and air quality. CHAPTER 4 and CHAPTER 5 describe the current state of knowledge about smoke contributions to poor air quality based on monitoring and modeling. CHAPTER 6 describes health and ecological effects associated with smoke and worsened air quality, but also recognizes that smoke can also have some positive impacts, such as stimulating flowering of some perennial grasses and herbs and contributing to climate cooling.

##### 2.3.4.2.2 Ash-Related Damages

Ash from fires, discussed in CHAPTER 6, can deposit on soils, water, vegetation, and man-made structures and vehicles. Ash deposition can lead to increased nutrient availability in soils, and depending on what types of materials are burned, can also lead to increased levels of metals. Ash deposition can also affect water quality, either directly through ash residues entering water bodies, or through increases in nutrient loadings that result from movement of excess nutrients through soils.

##### 2.3.4.2.3 Effects on Greenhouse Gas (GHG) Emissions

Fires result in the release of a number of GHGs, both from burning of trees and other woody biomass, as well as from soils. Greenhouse gases released include $CO_2$, $N_2O$, $NO_X$, and methane. Emissions are a function of climate, soil properties, and vegetation composition and management practices. Emissions of GHGs occur both during the fire, as well as longer-term, due to changes in soil and surface fuel carbon and nitrogen pool sizes, conversions from one vegetation type to another, and changes in soil moisture and temperature associated with canopy removal. There are differences in plume rise and fuels consumed between most wildfires and prescribed fires which result in substantially different areas of impact as well as potential entrainment into long-range transport and retention of GHGs in the upper atmosphere [see U.S. EPA (2012)]. A clear benefit of fuels treatments including prescribed fire, which affect wildfire risk, is the potential to improve long-term carbon sequestration [see CARB (2015)].

### 2.3.5 Programs to Mitigate Exposures and Impacts

Prescribed fires occur after extensive planning in an attempt to reduce population exposures to smoke and provide an opportunity to reduce smoke exposures of downwind communities through public health messaging campaigns. As a result, the ability of behavioral actions such as staying indoors or using N95 facemasks when outdoors to mitigate exposures can play an important role in reducing the health impacts associated with smoke emissions during prescribed fires. While there is some limited opportunity to use these types of behavioral actions during wildfires, prescribed fires provide the opportunity to increase those behaviors in at-risk populations through communication and public awareness activities. Likewise, communities can increase readiness for smoke during prescribed fires through public information messaging about nearby burning activity or through messaging campaigns to ensure populations, especially those at increased risk, are taking measures to protect themselves. Consideration of programs that increase awareness of prescribed fire events, including the projected path of smoke plumes, could have a large influence on reducing health impacts.

Wildfire smoke also has some opportunities for mitigation of exposures and effects. The implementation of the Interagency Wildland Fire Air Quality Response Program as authorized by PL 116-9 March 12, 2019. Page 617; Section 1114(f), as well as efforts by U.S. Environmental Protection Agency (U.S. EPA), state, tribal, and local air quality regulatory agencies and public health agencies warn the public and at-risk populations of wildfire smoke exposures and ways to mitigate impacts. Through these efforts, the public is becoming more aware of the risks of wildfire smoke exposure and air quality and health impacts. CHAPTER 6 (Section 6.3) provides a discussion of the various actions and interventions that can be employed by individuals to mitigate or reduce wildland fire smoke exposures.

### 2.3.6 Implementing the Conceptual Framework

Wildland fire results in a range of beneficial and detrimental effects, some of which can be quantified, while others are more difficult to quantify. Table 2-1 lists the categories of impacts associated with wildland fire, both the direct fire effects and those specific to smoke exposure, and highlights those effects that are the focus of the quantitative analyses that revolve around the case study fires (i.e., Timber Crater 6 and Rough Fires) examined within this assessment. The nature and magnitude of these effects will be dependent on the type of fire experienced, the vegetation affected, and the timescale, but the potential for these effects exists for both prescribed fires and wildfires. Effects can occur directly within the fire boundary, adjacent to the fire, or distant from the fire, for example impacts of smoke emissions on air quality or degradation of water quality. Additionally, effects can be within a few days, or over months or years. Effects can be positive or negative with positive effects providing some advantage, which could include restoring ecosystems or mitigating the risk or loss from a wildfire, while negative effects describe detrimental consequences from a fire, which could include damages to public health, property, or infrastructure. The conceptual framework outlined within this chapter described the linkages between the direct fire and smoke effects of wildland fire to lay the foundation for discussions in subsequent chapters that qualitatively and quantitatively evaluate the effects of prescribed fire and wildfire in an attempt to provide an overall comparison of the benefits and costs associated with different fire management strategies, with a focus on the smoke impacts.

**Table 2-1 Expected effects associated with wildland fire: quantified and unquantified for the case study analyses.**

| Categories of Expected Effects | |
|---|---|
| Unquantified Effects[a] | ***Firefighting*** |
| | • Firefighter safety |
| | • Firefighter injuries/fatalities |
| | • Firefighter health, both mental and physical |
| | ***Economic*** |
| | • Evacuations |
| | • Property (e.g., structures) |
| | • Property (e.g., loss of ecosystem services) |
| | • Timber and grazing |
| | • Infrastructure (e.g., powerlines, recreation, others) |
| | • Municipal watersheds (e.g., reservoirs, industry, agriculture, drinking) |
| | • Tourism (e.g., recreation, lodging, restaurants, etc.) |
| | • Aesthetics (e.g., property value, view shed, etc,) |
| | • Natural and cultural resources |
| | • Fuel reduction—cost effective method of treating acres |
| | • Fuel reduction—treatment opportunities not limited to local markets[b] |
| | ***Ecological*** |
| | • Ecological services including game and endangered species |
| | • Ecosystem health and resiliency |
| | • Restoration/maintenance of historic natural fire regime |
| | • Invasive species |
| | • Climate change (e.g., GHGs, carbon) |
| | • Redistribution of toxics and nutrients (e.g., mercury, metals, sulfur, nitrogen) |
| | • Soil and water quality and quantity |

**Table 2 1 (Continued): Expected effects associated with wildland fire: quantified and unquantified for the case study analyses.**

| Categories of Expected Effects | |
|---|---|
| Unquanti-fied Effects[a] (Cont.) | ***Public Health: Direct Fire*** |
| | • Injuries |
| | • Emergency department visits and hospital admissions |
| | • Premature mortality |
| Quantified Effects[c] | ***Air Quality*** |
| | • $PM_{2.5}$ concentrations |
| | • Ozone concentrations |
| | ***Public Health: Air Quality*** |
| | • Respiratory- and cardiovascular-related emergency department visits and hospital admissions |
| | • Premature mortality |

GHG = greenhouse gas; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm.

[a]Of these unquantified effects, some are not discussed in this assessment.

[b]This fuel reduction effect reflects the issue that in some locations fuel reduction options are limited by the lack of local markets for products such as merchantable timber of biomass, resulting in prescribed fire and chipping as the only fuel reduction options available. The presence of local markets reduces costs and increases the fuel reduction options available.

[c]Examining these effects represents the primary focus of this assessment.

See Section A.2 (Table A.2-1) for a more detailed version of this table that accounts for whether the effects listed result in positive or negative impacts due to prescribed fire and wildfire.

Fully implementing the conceptual framework detailed within this chapter requires a diverse set of data and models. The ultimate results would be a complete set of quantified, and in some cases monetized impacts, specifically health impacts and corresponding economic values, associated with each selected fire management strategy. However, for the purpose of this assessment the quantification is limited to the smoke impacts associated with different fire management strategies and reflects a comparison of only one area of negative effects and not a comprehensive, full accounting of both the negative effects along with the positive effects of wildland fire. Monetization is useful because it provides a consistent way to aggregate disparate effects. Economic theory and practice typically recommend discounting of benefits and costs that occur in the future to account for societal time preferences, e.g., benefits occurring today are in most cases valued higher than benefits occurring in the future (U.S. EPA, 2014). Because of uncertainty regarding when wildfires occur relative to when prescribed fires occur, it is challenging to determine the timeframes for comparing the two types of fires. For this assessment, we present undiscounted dollar values, which assumes that benefits and costs of fire management strategies all occur in the same current year. Comparisons would differ if prescribed fire effects are assumed to occur earlier in time than wildfire effects. A full accounting of comparisons between strategies would require aggregating all of the monetized benefits and damages for each fire management strategy, and then computing the expected value of damages using Equation 2-1, and differencing the expected values between strategies (e.g., fire management strategy *i* will have benefits compared with fire management strategy *j* if $EVi - EVj > 0$). However, given the limited availability of data to model many nonhealth endpoints, this assessment only aggregates the values of health endpoints associated with air quality changes due to smoke.

Net benefits can also be compared between fire management strategies. With a complete set of potential wildland vegetation management strategies, the optimal strategy will be the one with the highest net benefits. Even with an incomplete set, fire management strategy *i* is preferred to management strategy *j* if $NB_i > NB_j$.

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# CHAPTER 3 FIRE REGIMES, FIRE EFFECTS, AND A HISTORY OF FUELS AND FIRE MANAGEMENT IN DRY FORESTS OF THE PONDEROSA PINE REGION

## 3.1 Fire Regimes and Ecological Condition of Forests

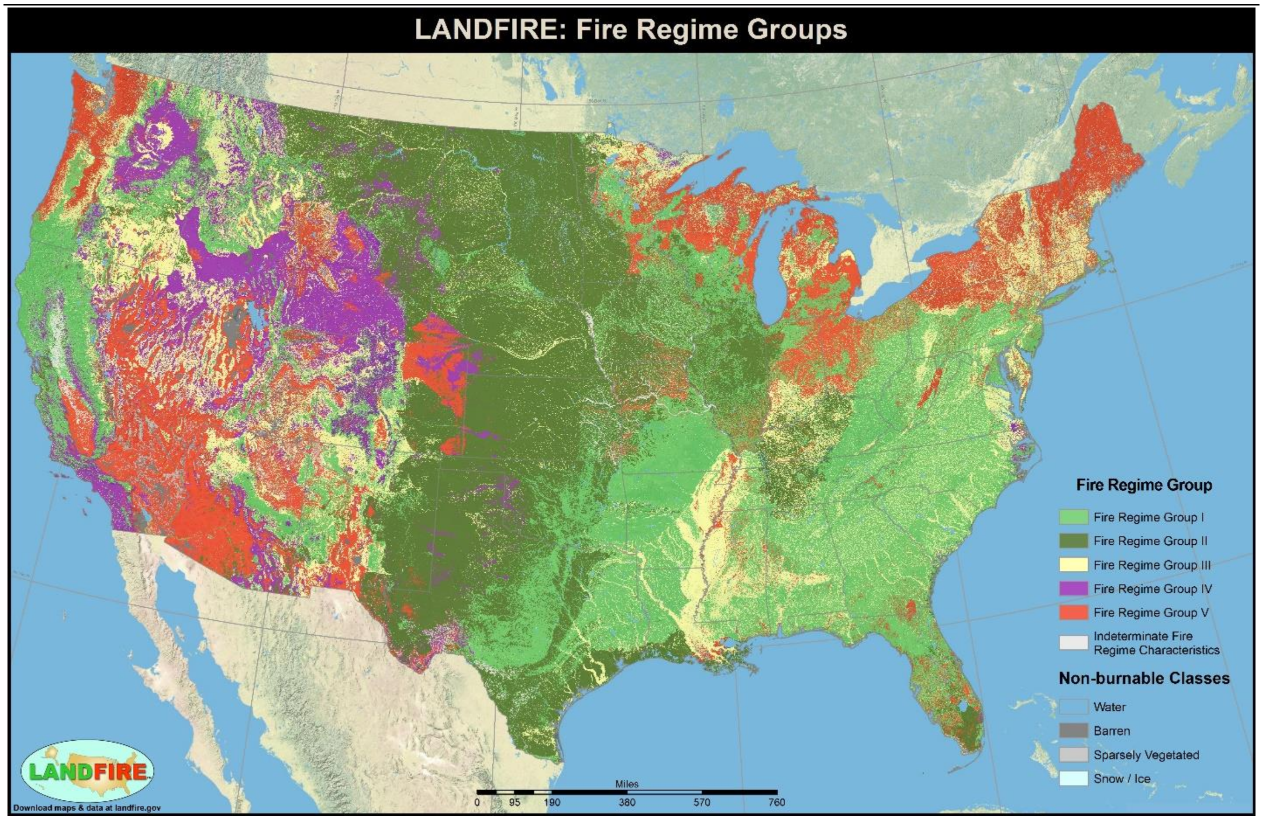
Fire regimes are patterns of fire size, intensity, severity, recurrence or frequency and the resulting ecological effects that are typical of vegetation assemblages in spatial scales from sites to broad regions of the county (Agee, 1993). They are typically based on historical patterns, based on human observation, ecological records, and geological records, depending on the length of available data, and they are temporally dynamic, depending on longer-term vegetation and climatic distributions, as well as on long periods of human interaction and resource use. Fire regimes have changed with climate over long time periods; they are likely changing now as well, although we are not able to define the changes while they are occurring. They influence forest recovery, succession, structure, and ecosystem functioning (Agee, 1993). Fire regimes are influenced largely by climate, vegetation types and by topographic and geologic features that either facilitate or restrict fire spread and vary by season and geographic region resulting from regional weather patterns (Taylor and Skinner, 1998; Agee, 1993).

There are numerous classification systems for describing fire regimes, often depending on the context and purpose of the classification system. The most used classifications consider the frequency, severity (or scale of ecological impacts) and a measure of spatial scale of wildfire in a natural or quasi-natural condition, although many other variables have been used in classification schemes [Ryan and Opperman (2013); Table 3-1, Figure 3-1]. Fire frequency, or the mean fire return interval, is a measure of how often fire returns, on average, to a specific area. There may be a wide range around this mean, which has important ecological implications for stand development and forest structure (Baker and Ehle, 2001). Landscape fire rotation, often used to characterize fire regimes, refers to the years required for a defined area to experience fire (Farris et al., 2010) and helps to smoothen out variations over space and time to help characterize typical fire regimes.

## Table 3-1 Fire regime groups and descriptions.

| Group | Frequency | Severity | Severity Description |
|---|---|---|---|
| I | 0−35 yr | Low/mixed | Generally low-severity fires replacing less than 25% of the dominant overstory vegetation; can include mixed-severity fires that replace up to 75% of the overstory |
| II | 0−35 yr | Replacement | High-severity fires replacing greater than 75% of the dominant overstory vegetation |
| III | 35−200 yr | Mixed/low | Generally mixed-severity can also include low-severity fires |
| IV | 35−200 yr | Replacement | High-severity fires |
| V | 200+ yr | Replacement/any severity | Generally replacement-severity; can include any severity type in this frequency range |

Source: Hann et al. (2008).




FRG = Fire Regime Group; LF = LANDFIRE.

Note: FRG definitions best approximate the definitions outlined in the Interagency Fire Regime Condition Class Guidebook and refined to create discrete, mutually exclusive criteria appropriate for use with LF's fire frequency and severity data products.

Source: LF (2012).

**Figure 3-1 Fire Regime Groups characterizing the presumed historical fire regimes within landscapes based on interactions between vegetation dynamics, fire spread, fire effects, and spatial context.**

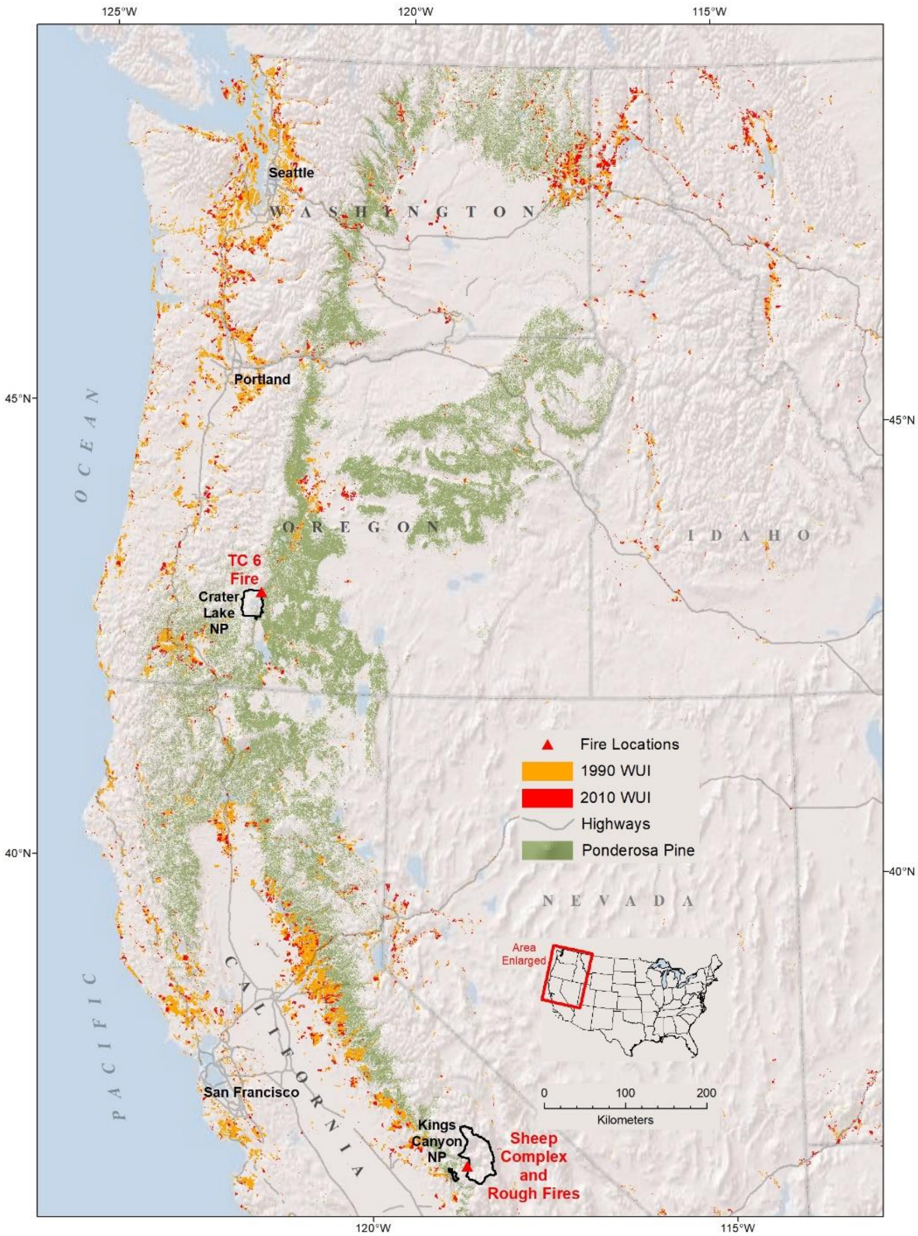
Fire severity is determined by either a visual estimate or measured assessment of fire effects on soils and vegetation (Table 3-1). Fire intensity, a major factor in severity, is a measure of heat or energy released (kW) per unit length (m) along the fireline and can be estimated by measuring flame length as the flaming front passes a known point (Rothermel and Deeming, 1980). High-intensity fires (e.g., long flame lengths), for example, result in more consumption and charring of surface fuel, increased exposure of soil and alteration of soil properties, and more damage and mortality of trees and other vegetation. While duration of burning at a given site has profound implications for fire severity and smoke production, duration is much more difficult to observe and to characterize than fire intensity.

### 3.1.1 Historic Fire Regimes in the Ponderosa Pine Region

This chapter focuses on the characterization of ponderosa pine ecosystems because they are very well understood and comprise a large portion of the ecosystem within the two case study areas that form the basis of the quantitative analyses within this assessment (see CHAPTER 5 and CHAPTER 8). At a finer resolution, the case studies do contain some different forest types as well as shrub, grass, and understory vegetation components. However, these areas represent much smaller areas than ponderosa pine and dry mixed conifer forest.

Historically, ponderosa pine (*Pinus ponderosa* P. & C. Lawson) forests and much of the adjacent dry mixed conifer zone experienced frequent, mixed to low-intensity fire (Agee, 1993). Periodic fires consumed accumulated fuels, thinned young seedlings and saplings, and consumed shrubs and herbaceous plant material, leaving the large, fire-resistant trees intact. Some individual large trees or small groups of large trees may have been directly killed or stressed by fire and later attacked and killed by bark beetles (Munger, 1917). This fire regime aligns geographically with the current distribution of ponderosa pine, which occupies 76,997 $km^2$ (14.7% of the land area) in Oregon and Washington, and approximately 94,200 $km^2$ (11% of the land area) in northern California (Figure 3-2). For the purposes of this assessment, the area occupied by these forests is collectively referred to as the ponderosa pine region.

The continental climate of the ponderosa pine region is semiarid and is largely controlled by a rain shadow effect from the Cascade, Coast and Sierra mountain ranges to the west. Annual summer droughts are a common characteristic as less than 20% of precipitation falls during May−September, based on precipitation data from the Parameter-Elevation Relationships on Independent Slopes Model (PRISM) Climate Group at Oregon State University (Daly et al., 2008). Historically, low-severity surface fires were more frequent and burned over larger areas compared to nondrought years (Hagmann et al., 2019; Johnston, 2017; Heyerdahl et al., 2008; McKenzie et al., 2004). However, drought is usually not the sole or ultimate cause of most tree mortality, but it interacts with pests and diseases, collectively termed biological disturbance agents (BDAs), to influence tree mortality (Kolb et al., 2016). These factors, drought and BDAs, account for much of the tree mortality throughout the region (Hessburg et al., 1994).




WUI = wildland–urban interface.

Source: https://lemma.forestry.oregonstate.edu LEMMA (2020).

Note: Distribution and expansion of the WUI (Radeloff et al., 2018) in Washington, Oregon and California has increased from 41,318 to 50,856 km$^2$ (23%) between 1990 to 2010 and is depicted in orange and red with approximately 8.3% of the WUI in the Ponderosa Pine Region as of 2010. The growth of the WUI in the ponderosa pine region, from 3,072 km$^2$ in 1990 to 4,211 km$^2$ in 2010 (37%), highlights how recent fire activity in dry fire prone forests impacts an expanding human population. Locations of the Timber Crater 6 and Rough fires are identified by red triangles.

**Figure 3-2 The ponderosa pine region as defined by the distribution of *Pinus ponderosa* in Oregon, Washington, and northern California (94,000 km$^2$, 11% of the land area shown) based on 2017 Gradient Nearest Neighbor maps.**

### 3.1.2 Historic Forest Conditions

Historically, forests in the ponderosa pine region consisted of multiaged stands with a structural backbone of large old-growth trees that persisted because of resistance to frequent and extensive fires, severe and prolonged droughts, and BDAs. Douglas fir (*Pseudotsuga menziesii* [Mirb.] Franco), grand fir (*Abies grandis* [Douglas ex D. Don] Lindl.), and white fir (*Abies concolor* [Gordon & Glend.] Lindl. ex Hildebr) are common associates of ponderosa pine at higher elevations across the region (Safford and Stevens, 2017; Franklin and Dyrness, 1988), while blending to pinyon and juniper woodlands at lower elevations (Miller et al., 2019). Presettlement forests throughout the region were characterized by open, park-like stands of large-diameter trees with a few seedlings and saplings in the understory. Stands were typically uneven-aged, with many stands containing a few large individual trees 400 to 600 years old (Youngblood et al., 2004; Arno et al., 1997). Historic photos show the open character of old growth ponderosa pine on the Klamath Indian Reservation in south-central Oregon in the early 20th century and current old growth (Figure 3-3).

Source: left, BIA photo; right, photo: PA Beedlow.

**Figure 3-3 Historic photo showing the open character of old growth ponderosa pine resulting from high-frequency, low-intensity fire on the Klamath Indian Reservation in south-central Oregon in the 1930s (left) and present-day ponderosa pine forest 10−15 years after natural fire Ochoco National Forest, central Oregon (right).**

### 3.1.3 Fire Influences on Forest Structure and Composition

Comparing forest conditions under a frequent low-severity fire regime with infrequent mixed- to high-severity fire illustrates how an open and heterogeneous structure historically resulted in resistant forest conditions over long time periods and across the ponderosa pine region. Patches of high-severity fire historically were small and rare (Heyerdahl et al., 2019; Merschel et al., 2018; Agee, 1993) because fire maintained low surface and canopy fuel loads (Johnston et al., 2016), there was heterogeneity in horizontal structure at fine (Churchill et al., 2013) and coarse scales (Hessburg et al., 2005), and because most trees were large and, consequently, fire-resistant (Hagmann et al., 2014, 2013).

### 3.1.4 Ecosystem Resilience/Resistance to Fire

Resilience is the capacity of an ecosystem to recover its essential characteristics following a disturbance, whereas resistance is the property of an ecosystem to remain essentially unchanged when disturbed. Resistance is often thought of as a component of resilience, but the two ecological processes are distinct mechanisms that maintain the essential characteristics of an ecosystem including taxonomic composition, structure, ecosystem function, and process rates (Holling, 1973). Within the ponderosa pine region, open forest structure and fine scale heterogeneity predominated historically, and this conveyed resistance to fire and other disturbances at fine scales (Koontz et al., 2020), as well as broadly across entire landscapes (Hessburg et al., 2005). However, after years of fire exclusion, in addition to logging and livestock grazing, low intensity surface fires have been excluded in many areas, resulting in dense stands that show both reduced resistance and resilience because of changes in species composition (Busse et al., 2009). Extreme severe fire is now much more likely to occur, reflecting decreased resistance.

### 3.1.5 Changes to Historic Fire Regimes

#### 3.1.5.1 Land Management Practices

Forest ecosystems in the ponderosa pine region have undergone structural and functional changes in the last 140 years since settlement (Hessburg and Agee, 2003). Heavy grazing in the late 1800s and early 1900s, active fire suppression after the 1910 fires, and other land uses have disrupted the natural fire regime in these ecosystems. Tree establishment and survival increased in the late 19th and early 20th centuries resulting in denser forests characterized by increased homogeneity in horizontal structure, increased canopy layering and connectivity, inter-tree competition, and canopy cover. This densification combined with widespread logging of large and old fire-resistant trees (Naficy et al., 2010; Hessburg and Agee, 2003) contributed to mesophication—a shift from drought and fire-resistant shade intolerant species to shade tolerant species adapted to competition but not as resistant to drought and fire (Nowacki and Abrams, 2008). Aggressive fire suppression since 1910 ensured that densification and mesophication continued to the present conditions. The forests of today are the cumulative result of tree establishment and growth versus mortality from drought, pests and diseases, fire, and land management [e.g., timber harvesting, thinning, prescribed fire; Merschel et al. (2021)].

#### 3.1.5.2 Habitat Fragmentation from Human Population Growth

Wildfires pose the greatest risk to people in the wildland–urban interface (WUI)—the area where houses are in or near wildland vegetation (Radeloff et al., 2005). It is the fastest growing land use type in the conterminous U.S. From 1990 to 2010 new houses in the WUI increased by 41%, from 30.8 to 43.4 million and land area increased 33%, from 581,000 to 770,000 $km^2$ (Radeloff et al., 2018). A more current study estimates ~49 million residential homes in the WUI, a number that has been increasing by roughly 350,000 houses per year over the last two decades (Burke et al., 2021). In the ponderosa pine region of Oregon, Washington, and California (Figure 3-2) the land area of WUI increased by 37% between 1990 and 2010 to 4,211 $km^2$.

#### 3.1.5.3 Invasive Species and Encroachment

Invasive species can establish permanency within ponderosa pine landscapes, but less frequently than within other biomes. The conditions required for invasive species to dominate ponderosa pine landscapes is complex. Many site features favor invasive plant suppression such as frequent small to moderate fires, fire resistant trees, rugged terrain, and high elevation (Zouhar et al., 2008). The establishment of invasive species within ponderosa pine region has been minimal, likely due to "less activity by humans, relatively intact shrub and tree canopies, [and] harsh climates"(Zouhar et al., 2008). Sites that do contain abundant levels of invasive plants have usually been disturbed first by human activity (Keeley et al., 2003; Moore and Gerlagh, 2001). Moderating fire intensity and targeting areas of high severity for remediation may reduce post-fire invasive plant outbreaks (Symstad et al., 2014).

#### 3.1.5.4 Weather and Changing Climatic Conditions

Topography, fire weather, and fuels have generally not limited chronic low-severity fire even in relatively cool-moist environments where relatively fire susceptible Douglas fir and true fir (*Abies* spp.) were common prior to fire exclusion (Hagmann et al., 2019; Merschel et al., 2018; Johnston et al., 2016; Heyerdahl et al., 2008). However, in the last 30 to 35 years, the West has seen a steady rise in the intensity of wildfires as well as area burned, tied to human-caused climate change (Goss et al., 2020). Drought conditions occurred in 15 of 18 years during 2000−2017 as air temperature was increasing at 0.3°C/decade (Abatzoglou and Williams, 2016). The years from 2000−2018 contained the driest 19-year period in western North America since the late 1500s (Williams et al., 2020). Recent drought in western North America was partially a product of natural variability, but its concurrence with anthropogenic warming resulted in intensity and duration on par with the most extreme drought events since 800 CE (Williams et al., 2020). As climate continues to warm in the 21st century, drought and related impacts to forests are projected to increase (Luce et al., 2016). Further, increasing drought severity in combination with climate-driven fungal pathogens and insect pests are exacerbating the fire hazard (Allen et al., 2019).

Historic fire regimes were compiled locally, regionally, and nationally, with extensive records, studies, and modelling. Changes observed in the past few decades are ongoing. Mapping and characterizing the changes on a large scale would likely become obsolete before this could be completed. Representation of projected future climate and expected fire regimes is important, but well beyond the scope of this assessment.

## 3.2 Land Management Approaches to Reducing Fire Risks

Fire is an important tool to improve forest conditions, reduce fuels and decrease the threat of large, high-severity wildland fires (Vaillant and Reinhardt, 2017). Fire managers have used natural ignitions as a key component in the restoration of historical forest conditions and fuel loadings. The 2009 Policy Guidance (FEC, 2009) provided federal land management agencies and their state partners greater flexibility to use natural ignitions to meet resource objectives through strategies other than full suppression. Though some land managers have increasingly used wildfire to meet resource objectives since the 1970s (Hunter and Robles, 2020; Collins et al., 2007), managers more commonly resort to full suppression strategies—a result of current land-management policies and local land use planning (Meyer et al., 2015; Thompson et al., 2013). However, land management and planning policies are beginning to be revised to be more inclusive of using wildfire to meet resource objectives.

### 3.2.1 Need for Fuel Treatments

With increasing growth of the WUI, long-term suppression of wildfires and resulting forest changes, and an era of increasing drought, wildfire has become a profound ecological and social issue in forests formerly dominated by frequent low intensity wildfires (Moritz et al., 2014). In response to decades of fire suppression, resulting in a fire deficit, and increasing periods of drought, wildfires have tended to become both larger and more severe. Compared to the area burned historically, there exists today an enormous fire deficit in the region, especially for low-severity fire. The fire deficit extends to a vast portion of dry forests of the conterminous U.S. (Kolden, 2019). Historically, open forests characterized by larger trees was the most common structural condition in the ponderosa pine region (Hagmann et al., 2014, 2013). However, in some high elevation and alpine forests, humid temperate forests, and shrublands, there may not be a deficit, and may indeed be a surplus of fire; this is beyond the scope of the current assessment and the two case studies. Tree regeneration and growth in the absence of frequent low-intensity fire in contemporary times has resulted in the loss of open resistant forest structure and composition, sparse woodlands, and nonforest cover (Stevens-Rumann et al., 2018). Wildfires in these denser forests tend to be more severe and have a greater chance of converting forested areas to different vegetation types, such as becoming shrublands in drier areas (Moreira et al., 2020; Parks and Abatzoglou, 2020).

### 3.2.2 Land Management Activities Affect Fire Behavior

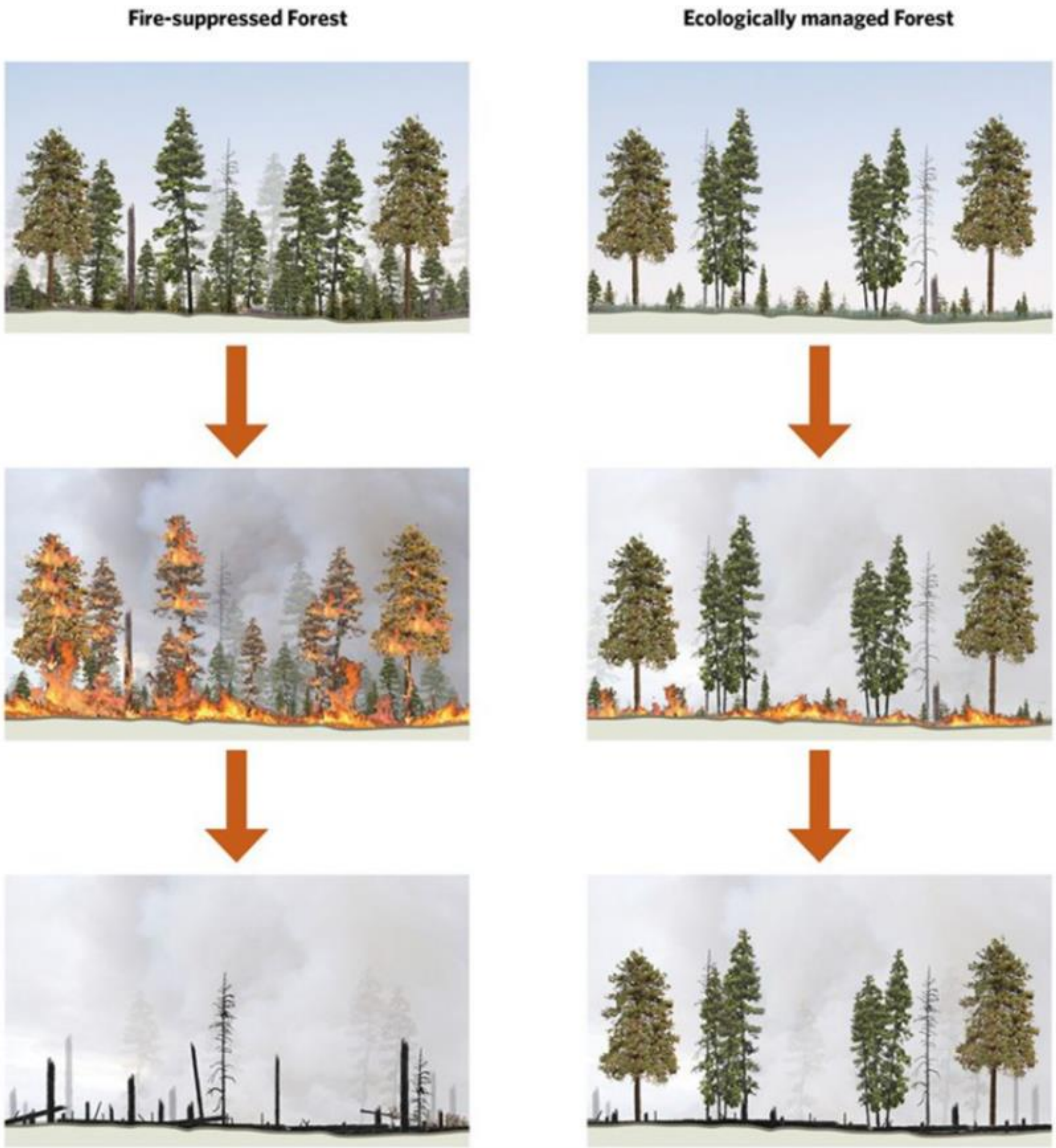
Forest policy and management practices are slowly changing from predominantly fire suppression to managing fire and associated risks to communities (Thompson et al., 2018; Ingalsbee and Raja, 2015). Prior to Euro-American settlement, many dry forests of the western U.S. were maintained by frequent low-to-moderate severity fires (i.e., cultural fires) often set by indigenous tribes (Hessburg et al., 2005). Native American tribes used cultural fires to purposely burn forests and grasslands to promote habitat diversity, environmental stability, predictability, and maintenance of ecotones, but perhaps the most important effect may have been the lack of advanced fire suppression technology (Raish et al., 2005). The absence of fire suppression allowed the natural progression of wildfires, both lightening and human caused, across the landscape. Over the last 140 years, forests in the ponderosa pine region have changed immensely and bear little resemblance to their presettlement condition. The original old-growth ponderosa pine forests were once considered an endless resource to early pioneers and settlers, and the vast "yellow pine" forests were utilized to fuel economic growth and the development of western North America. Past and current land use activities along with active fire suppression eliminated natural surface fires from these forests.

Fire exclusion over the last century in ponderosa pine forests has allowed for the buildup of surface fuels on the forest floor and shrub cover and tree regeneration to increase. This buildup has created "fuel ladders" where surface fuels are now connected to the overstory canopy by dense understory and mid-story saplings and medium-sized trees. As a result, it is easier for surface fires to move up and torch tree crowns and, under the right weather conditions and topographic setting, support active crown-to-crown fire spread.

Removing accumulated surface fuels or targeting the removal of specific brush fuels (such as bitterbrush [*Purshia tridentata* (Pursh) DC.] because of its high energy content), reduces flame lengths making it more difficult to initiate torching of tree crowns. Also, the higher the base of tree crowns, the more difficult it is for surface flames to torch tree crowns. Once a fire begins torching and moving up into the canopy, the rate of spread and density of the crowns determines the likelihood of an actively moving crown fire. Increasing the space between tree crowns reduces the ability for fire to spread from tree crown to tree crown and allows a crown fire to transition back to a surface fire.

Currently, the forest area being managed to reduce density, restore large ponderosa pine trees, and reintroduce low-intensity, frequent fire is very small compared to the forest area experiencing continued densification and succession. Fire is not being adopted into management practices at a scale necessary to affect the fire deficit in the western U.S. and reduce the potential for more wildfire disasters; the area burned by prescribed fire has actually decreased in the Pacific Northwest from 1998−2018 (Kolden, 2019).

Land Managers have tools and methods to improve fire resilience and resistance in the ponderosa pine region: these include reducing surface fuels, removing ladder fuels, leaving large, fire resistant trees, and spacing tree crowns (see CHAPTER 7 for economic considerations). These conditions can be achieved with a variety of methods including prescribed fire, use of naturally ignited wildfire to achieve land management objectives, mechanical thinning, and biological control (Agee and Skinner, 2005). The use of multiple tools to reintroduce fire as a natural process in fire-prone forests has come to be known as ecological forestry (Kelsey, 2019) and involves targeted removal of forest fuels plus implementation of prescribed fire and managed wildfire where it is safe to do so (Figure 3-4).




Note: Fire-suppressed forest (left): Forests become dense with thickets of young trees and shrubs in the understory and are prone to high-severity fires that can kill most of the trees. Ecologically managed forest (right): Strategic thinning the understory can reduce overall fuel load so fire can safely be reintroduced to maintain healthy forests. (Kelsey, 2019).



### Figure 3-4 Comparison of differences between a fire-suppressed and ecologically managed forest.

#### 3.2.2.1 Prescribed Fire

Prescribed fire is one of the most widely advocated management practices for meeting land management goals and objectives and has a long and rich tradition rooted in indigenous and local ecological knowledge. The scientific literature has repeatedly reported that prescribed fire is often the most effective means to reduce fuels and wildfire hazard in order to restore sustainable ecological functioning to fire-adapted ecosystems in the U.S. following a century of fire suppression (Kolden, 2019).

As defined in CHAPTER 2, a prescribed fire is "any fire intentionally ignited by management actions in accordance with applicable laws, policies, and regulations to meet specific land or resource management objectives" (U.S. EPA, 2020). Prescribed fire is used on the landscape to remove accumulated surface fuels, consume slash generated from thinning activities, kill and thin out encroaching trees in the understory, and rejuvenate herbaceous plants and shrubs (Sackett and Haase, 1998; Walstad et al., 1990; Ffolliott and Thorud, 1977). Prescribed fire also scorches and kills lower branches of trees, which, in the long run, results in lifting the canopy much like pruning, increasing the height from the forest floor to the lower canopy and increasing fire resistance (Figure 3-5).

Source: Photo: PA Beedlow.

**Figure 3-5 Prescribed fire in ponderosa pine, Deschutes National Forest.**

Periodic burning can prevent the development of fuel ladders and can be used to maintain fire-resilient stands. However, in most forests of the ponderosa pine region prescribed fire is limited as an initial treatment to reduce fuel loads because of heavy accumulations of surface and ladder fuels. In many cases, other mechanical treatments are needed prior to prescribed fire to reduce fuels to a level that will allow fire to be used without unnecessary damage to the forest.

The ability to control fire while minimizing human exposure to smoke and achieving the desired ecological results are central goals of prescribed burning (Long et al., 2018). On federal and most state lands, prescribed fire is only used after thorough preplanning and only by highly trained and experienced professionals (NWCG, 2017). Go/no-go checklists are used to determine compliance with policies and the prescribed fire plan parameters. Based on these guidelines, prescribed fire is only implemented when weather conditions are favorable, such as good smoke clearance conditions, moderate temperatures or even dry fuel conditions that result in rapid consumption and ventilation, and an incoming cool/moist weather pattern. Further, burning when smoke is not being produced by many wildfires over a large area is favored to reduce the magnitude and duration of smoke exposure. In the much of the western U.S, spring or after the start of fall rain provide good opportunities to manage wildfires due to environmental conditions resulting in low-severity, shorter duration fires. In the ponderosa pine region, most prescribed burns are conducted in the spring and late fall because personnel are available and weather conditions are favorable.

#### 3.2.2.2 Mechanical Treatments

Prescribed fire as a restoration tool, while often the cheapest to implement, is not practical in many cases due to limited burning seasons, excessive accumulation of fuel due to fire exclusion, concerns over potential undesirable fire effects, concerns about human exposure to smoke, visibility, and the chance that a fire will escape and cause damage. Mechanical treatments can create a variety of uneven-aged or even-aged stand structures depending on the desired treatment goals (e.g., fuel reduction to meet fire behavior goals), wildlife habitat maintenance requirements (e.g., for endangered species), and restoration of spatial and structural condition (Huggett et al., 2008). They require equipment as well as plans for disposal or utilization of significant quantities of small trees (Agee and Skinner, 2005).

How the residual wood from the thinning operations is disposed can have a large impact on surface fuel availability with chipping or burning of the unusable tops of trees having the greatest impact on reducing fuel loads. Mechanical treatments include activities, such as cutting and piling or stacking trees, cutting and piling brush, pruning lower branches of trees, and creating fuel breaks based on treatment objectives. Typically, mechanical treatments are emphasized in the WUI, while both mechanical and fire treatments, alone or in combination, are emphasized in adjacent lands from which wildland fire might spread into the WUI (Barros et al., 2019).

#### 3.2.2.3 Biological and Chemical Control

Biological control involves the intentional use of domestic animals, insects, nematodes, mites, or pathogenic agents such as bacteria or fungus that can cause diseases in plants to reduce or eliminate vegetation. Biological controls are used mostly to control invasive plants but can be used to control native vegetation for fire management purposes. For instance, cattle may be used for target grazing in defined areas for the creation of fuel breaks on rangelands and in some instances in forested lands.

In addition to natural agents, chemical agents, such as herbicides can also be used to kill or injure plants to meet land management objectives. Herbicides can be categorized as selective or nonselective. Selective herbicides kill only a specific type of plant, such as broad-leaved plants, while nonselective can kill all plants. Only those herbicides approved for use can be used to manipulate vegetation to meet land management goals and objectives.

#### 3.2.2.4 Natural Ignitions

Remote forest areas as well as designated wilderness areas and national parks provide the best opportunities for taking advantage of natural ignitions to reduce fuel loads. While fire managers may choose to suppress fire inside or outside of wilderness areas, it is also federal policy to use fire “to protect, maintain, and enhance resources and, as nearly as possible, be allowed to function in its natural ecological role” (FEC, 2009). The very definition of wilderness in the Wilderness Act of 1964, as an area “managed so as to preserve its natural conditions and which generally appears to have been affected primarily by the forces of nature” aligns closely with federal fire policy and thus are often an excellent location to achieve this goal. Moreover, wilderness area ignitions are often in steep, rugged terrain too dangerous for firefighters to attack directly or limit in the technologies and equipment that can be deployed.

Agencies permit lightning-caused fires to play a natural ecological role to reduce the risks and consequences of wildfire both within and outside wilderness areas. Fire managers seek to prevent fires from causing damage to nearby communities. In pursuit of that goal, Minimum Impact Suppression Techniques are implemented that cause the least alteration of the wilderness resource and the least disturbance to the land surface, air quality, and visitor solitude (USFS, 2007). The initial response to lightning caused wildfires is suppression if they occur in a landscape without a fire management plan, do not meet certain conditions, or cannot achieve land management objectives.

## 3.3 Forest Characteristics for Timber Crater 6 (TC6) and the Rough Fires

This assessment focuses on a quantitative analysis of the air quality and associated health impacts of smoke by examining two case study fires (see CHAPTER 1), both of which occurred in the western

U.S.: (1) the Timber Crater 6 (TC6) Fire that occurred from July 21−26, 2018 in Oregon; and the (2) Rough Fire that occurred from July 31 to October 1, 2015, in California. The Timber Crater 6 Fire burned approximately 3,000 acres in Crater Lake National Park from July 21 to July 26, 2018. The Rough fire burned in parts of the Sierra National Forest, Sequoia National Forest, and Kings Canyon National Park between July 31 and October 1, 2015 (https://www.nps.gov/seki/learn/nature/rough-fire-interactive-map.htm), burning approximately 150,000 acres. These fires were chosen as case studies because they were on federal land previously subjected to fuel reduction management. Both areas are in dry forests characteristic of the ponderosa pine region. The following sections describe the forest characteristics of the case study areas. Additional details on the burn characteristics of each case study fire are provided in CHAPTER 5.

### 3.3.1 Timber Crater 6 (TC6): Crater Lake National Park/Fremont-Winema National Forest

Crater Lake National Park spans the divide of the Cascade Mountains in central Oregon. Forests in the western part follow an elevational gradient from low elevation Douglas fir forests, to mixed conifer forests dominated by red fir (*Abies magnifica* A. Murr.), to mountain hemlock (*Tsuga mertensiana* [Bong.] Carriere) dominated stands at high elevation (Forrestel et al., 2017). The eastern portions of the park are dominated by ponderosa pine grading into mix-conifer forests at higher elevations. Forests in which ponderosa pine is a dominant tree principally occur up to 1,675 m elevation (Adamus et al., 2013). Ponderosa pine forests can contain a mixture of ponderosa pine, white fir (*Abies concolor* [Gord. & Glend.] Lindl. ex. Hildebr.), and scattered sugar pine (*Pinus lambertiana* Douglas) and Douglas fir. Where ponderosa pine shares dominance with these species, the forests can be called mixed conifer. On the east side of the park, lodgepole pine (*Pinus contorta var. murrayana* [Grev. & Balf.] Engelm.) is a common associate with ponderosa pine, and understory species may include the Great Basin shrubs, including antelope bitterbrush (*Purshia tridentata* [Pursh] DC.), the montane chaparral shrub, greenleaf manzanita (*Arctostaphylos patula* Greene), and a greater abundance of native grasses.

The Timber Crater 6 Fire started with a lightning strike in the northeast portion of the park on July 15, 2018 and within 4 days spread into a nearby section of the Fremont-Winema National Forest (Figure 3-6). The fire spread to property where the U.S. Forest Service had invested in fuel treatments starting in the 1990s. Treatments included mowing and small tree thinning followed by pile burnings and prescribed burning. The fire had the potential to burn about 81 $km^2$, but because of the fuel treatments, it was contained to 12.7 $km^2$ (Delamarter, 2019).

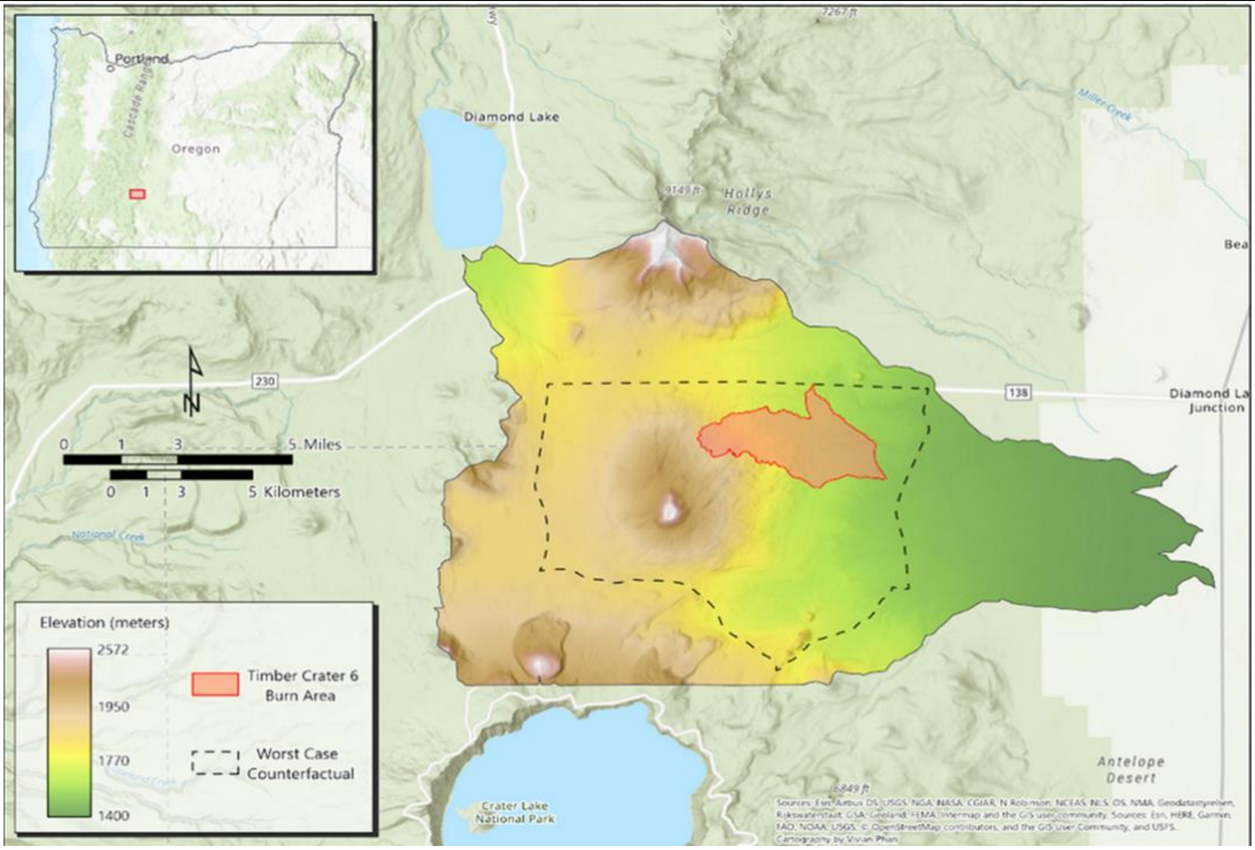



**Figure 3-6** **Timber Crater 6 (TC6) Fire, Crater Lake National Park, and adjacent Fremont-Winema National Forest.**

### 3.3.2 Rough Fire: Sierra and Sequoia National Forests and Kings Canyon National Park

In the Sierra Nevada, especially on the west slope exposed to moisture off the ocean, much of the area where ponderosa pine occurs is considered mixed conifer (Safford and Stevens, 2017), often referred to in California as Yellow Pine Mixed Conifer. The Rough fire burned a substantial area of the Kings Canyon, one of the deepest canyons in California, in a footprint that spanned an elevational gradient of more than 2,100 m, from ~300 m above sea level (ASL) to just under 2,500 m ASL (Figure 3-7). On the western side of the southern Sierra Nevada Mountain range, which is exposed to storms and prevailing winds coming off the Pacific Ocean, this area of the canyon encompasses a steep precipitation gradient, with a distinct Mediterranean annual pattern allowing for high productivity, but also requiring robust summer drought tolerance. This precipitation gradient and moisture availability pattern in turn drives a diverse range of vegetation assemblages and growth strategies, from grassland and oak woodlands in the lower elevations (~300 to 1,200 m ASL) to highly productive yellow pine (ponderosa pine) mixed conifer (including giant sequoia [*Sequoiadendron giganteum* (Lindl.)] Buchholz) in the mid-elevations (1,200 to 2,100 m ASL) to red fir and lodgepole pine typical of boreal forest in the higher elevations (over 2,100 m ASL) of the Rough Fire footprint. Pure ponderosa pine stands occur in the lower to mid-elevations but comprise a relatively small fraction (~7%) of the total area burned by the Rough Fire. However, ponderosa pine (and its higher-elevation cousin, the Jeffrey pine) is often an important component of the mixed conifer zone, which comprises a majority (~33%) of the forested area burned by the Rough Fire (Huang et al., 2018; Safford and Stevens, 2017).

Throughout this complex and highly heterogeneous matrix of vegetation types (Figure 3-8), fuels generally increase with elevation from under 2,000 mg/km$^2$ in the lower elevation oak woodlands and grasslands to over 18,000 mg/km$^2$ in the mixed conifer and upper montane vegetation of the mid-upper elevations. The overall amount of those fuels was also likely enhanced by an unprecedented mortality event, wherein about 30% of the area burned by the 2015 Rough Fire had experienced at least 10% canopy cover loss due to tree mortality from 2011−2014 (and likely much more in some of the ponderosa pine dominated stands). Ponderosa pine and mixed conifer stands in the lower to mid- elevations in particular appeared to have suffered the most uniformly severe mortality (Fettig et al., 2019; Paz-Kagan et al., 2017). Though the proximate cause of this mortality was likely a bark beetle infestation that opportunistically attacked trees weakened by several years of antecedent drought from 2012 through 2015 (Restaino et al., 2019), these lower elevations also experienced chronically phytotoxic levels of ozone and nitrogen deposition for decades [e.g., Yates et al. (2020); Panek et al. (2013); Peterson et al. (1991)], which likely contributed to their susceptibility to those beetles and the drought(Jones et al., 2004). By the time the Rough Fire burned in 2015, this mortality event was in the “red needle” phase mortality event, wherein the tree canopy consisted of dead or dry needles and twigs, which contributed to increased crown fire potential and higher forest fire severity (Stephens et al., 2018; USFS, 2016). Torching potential and ember production were also thought to have occurred in areas affected by tree mortality (Reiner, 2017). In the years post-fire, dead trees not consumed in the fire decay and the coarser “gray phase” fuels fall to the ground increasing fuel loads potentially contributing to larger scale, “mass fire” events similar the more recent 2020 Creek Fire (Stephens et al., 2018).

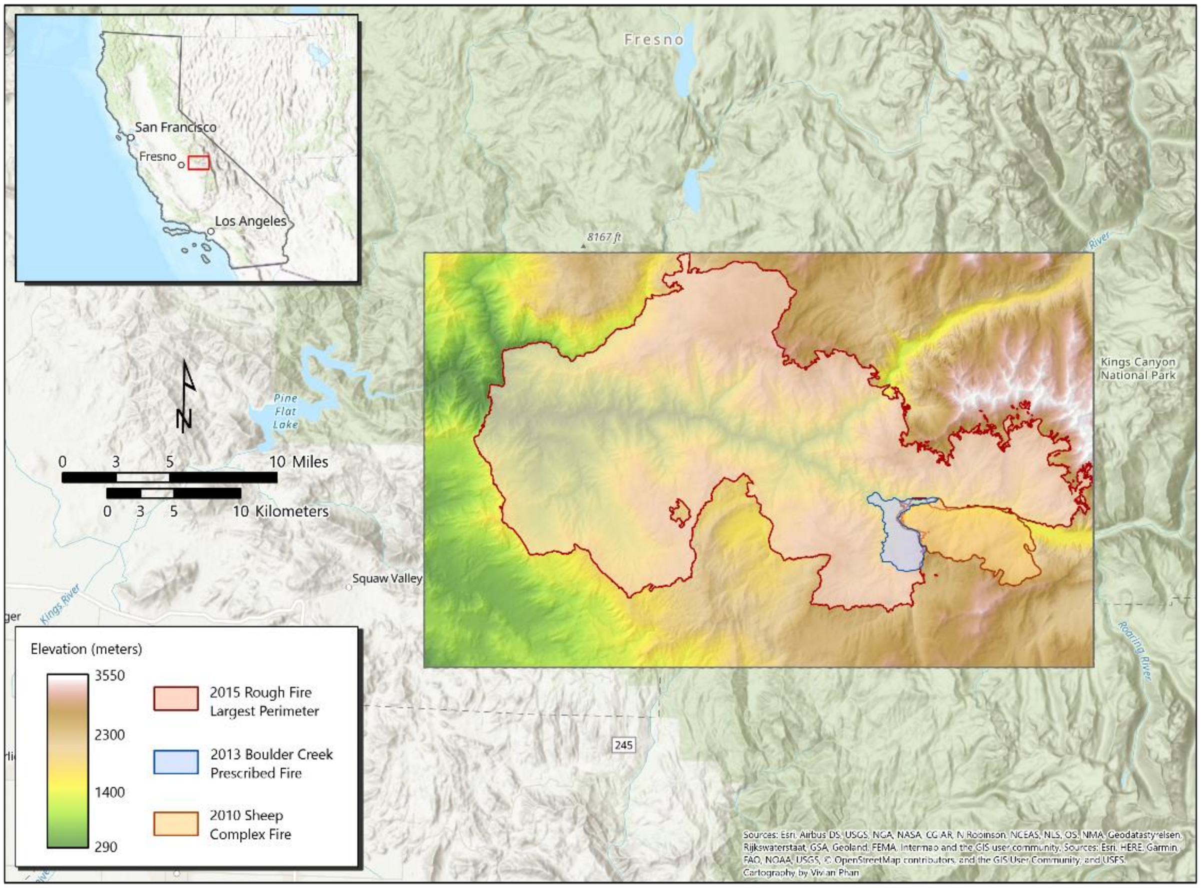
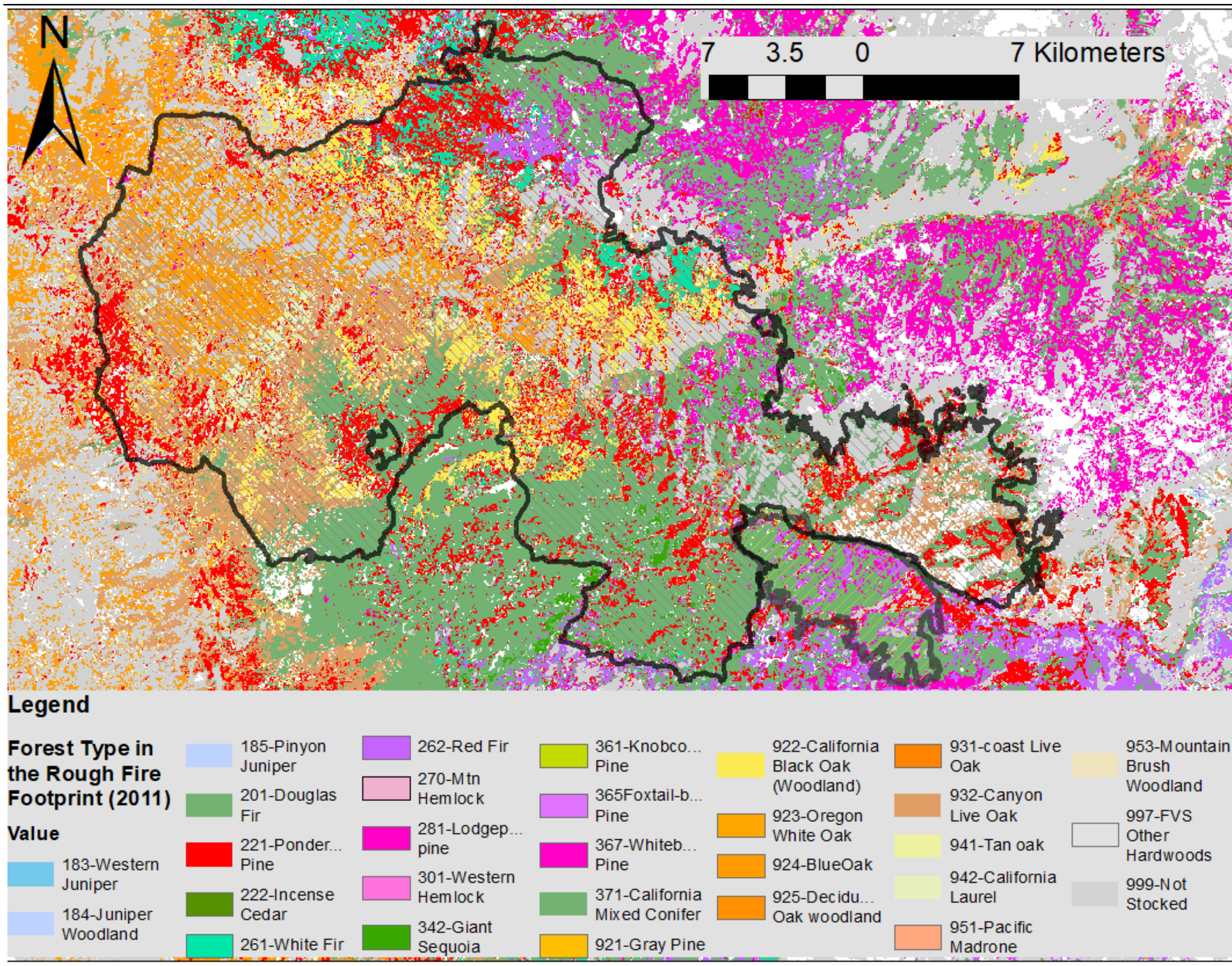



**Figure 3-7** **Rough Fire: Sierra and Sequoia National Forests and Kings Canyon National Park.**




Note: based on Forest Inventory and Analysis (FIA) and satellite data, see Huang et al. (2018), copyright permission pending.

**Figure 3-8 Tree species maps for the area of the Rough Fire.**

## 3.4 Conclusions

From an ecological perspective, restoration of frequent low-severity fire is an essential to restoring sustainable ecosystems in the dry forests of the ponderosa pine region. However, extensive densification and mesophication of these dry ecosystems due to land management practices in the 20th century, followed by an increase in wildland fire frequency and severity, drought, invasive species, pests and diseases, as well as the rapid expansion of the WUI pose serious ecological and socioeconomic challenges to human wellbeing in the 21st century. Key to living with fire in the ponderosa pine region is an all-lands and all ownerships approach to forest management planning that helps determine where prescribed fire and mechanical treatments are appropriate and should be prioritized, and where fires can safely be allowed to burn (Dunn et al., 2020).

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# CHAPTER 4 AIR QUALITY MONITORING OF WILDLAND FIRE SMOKE

## 4.1 Introduction

Wildland fires (prescribed fire and wildfire) can produce significant air pollution emissions which may pose health risks to fire crews, first responders, and nearby residents, as well as downwind populations (see CHAPTER 5, CHAPTER 6, CHAPTER 7, CHAPTER 8). Wildland fire smoke is a complex mixture of thousands of different organic, inorganic, gaseous, and particulate phase compounds (Reisen et al., 2015). The primary constituents of emitted wildland fire smoke that impact air quality are fine particulate matter (PM) with a nominal mean aerodynamic diameter less than or equal to 2.5 µm ($PM_{2.5}$), carbon monoxide (CO), oxides of nitrogen, and volatile organic compounds Urbanski (2014). The secondary photochemical formation of $PM_{2.5}$ and ozone ($O_3$) from wildland fire emission precursors is also a concern (Liu et al., 2017; Alvarado et al., 2015; Jaffe and Wigder, 2012).

The U.S. Environmental Protection Agency (U.S. EPA) and its partners at state, local and tribal monitoring agencies manage several routine regulatory monitoring networks. Each of these ambient air monitoring networks have regulatory requirements and policy objectives that dictate decisions on the location and pollutants measured at each site. The implementation of the network objectives results in monitoring sites that are predominantly concentrated in larger population centers where anthropogenic air pollution sources are concentrated (Figure 4-1a). The relatively high cost of establishing and maintaining regulatory monitoring sites limits their overall numbers and reach into smaller and more remote communities. The Code of Federal Regulations [CFR; U.S. EPA (2016)] require the use of U.S. EPA designated Federal Reference Method (FRM) or Federal Equivalent Method (FEM) instruments for regulatory National Ambient Air Quality Standards (NAAQS) compliance monitoring. However, some flexibility is provided to monitoring agencies in using nonregulatory PM measurements when reporting the U.S. EPA Air Quality Index (AQI) as detailed in 40 CFR Appendix G to Part 58. Although there are efforts by individual state, local, and tribal monitoring agencies, U.S. EPA currently has no national air quality monitoring programs specifically designed to evaluate wildland fire smoke impacts. There are no national programs designed to require the establishment of new sites in smoke prone areas, no grant opportunities to otherwise encourage optional supplemental smoke monitoring, and no program to evaluate the performance of designated FRM/FEM monitoring instruments in smoke. As a result, even though U.S. EPA and its state, local, and tribal partners developed and maintain a relatively advanced set of regulatory air monitoring networks, remote wildland firefighter camps and smaller population centers impacted by smoke in most instances lack adequate observational air quality data, and those instances where regulatory monitors are present the accuracy of the reported smoke impacted air pollution data is uncertain (Landis et al., 2017; Long et al., In Press).

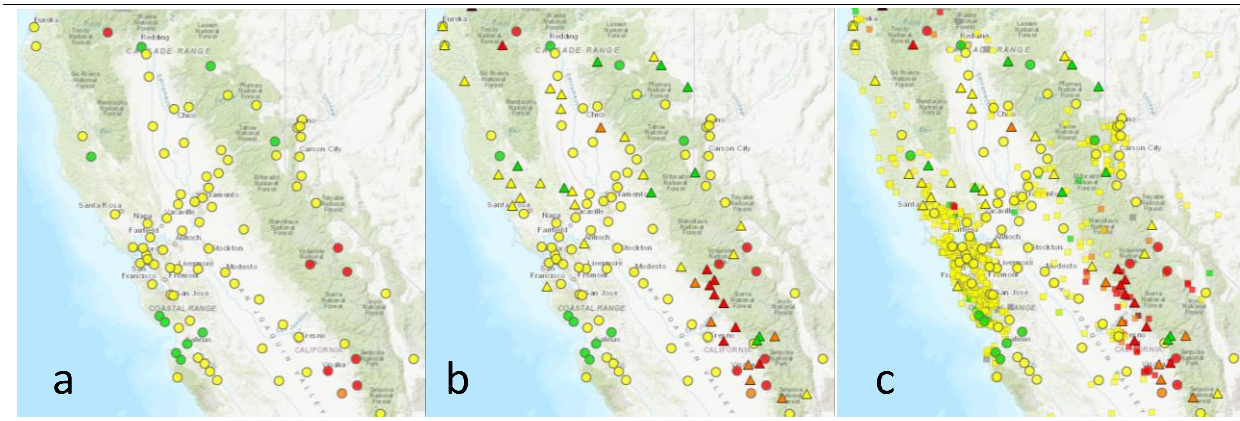



**Figure 4-1 AirNow Fire and Smoke site displaying the October 7, 2020 layers of $PM_{2.5}$ monitors across central California for (a) regulatory Federal Equivalent Method (FEM) instruments [circles], (b) with additional California Air Resources Board (CARB) and U.S. Forest Service (USFS) temporary monitors [triangles], and (c) with the addition of PurpleAir sensors [squares].**

The impact of wildland fire smoke plumes on specific downwind locations are influenced by the behavior and location of the fire, how the emissions are lofted into the atmosphere, and subsequent transport, chemical transformation, and dispersion. Surface level smoke impacts can be highly spatially/temporally variable and air quality monitoring sites within affected regions may not adequately represent the very dynamic temporal evolution of smoke impacts beyond its immediate location. During many large wildfire incidents, the U.S. Forest Service (USFS) led Interagency Wildland Fire Air Quality Response Program (IWFAQRP) augments long-term regulatory monitoring networks with temporary nonregulatory air quality monitors dispatched with Air Resource Advisors [ARAs; Figure 4-1b; USFS (2020b, 2020a)]. In addition, USFS regional offices, states, local, and tribal agencies also maintain and deploy nonregulatory samplers for monitoring smoke impacts from wildfires and prescribed burns. However, the cost, technical expertise required, and need for electrical power/data telemetry infrastructure generally limits the number and location of temporary nonregulatory monitors that are deployed. Federal, state, local, and tribal agencies as well as school districts, universities, and private citizens have deployed nonregulatory air quality sensors to monitor general air quality. These sensors present the opportunity to qualitatively improve the spatial variability of wildland fire smoke impacts due to their ability to be deployed in large numbers [Figure 4-1c; 2B Tech (2021); Clarity (2021); PurpleAir (2021); Gupta et al. (2018)].

Information on general ambient air quality, the impact of wildland fire smoke on current ambient air quality conditions, and air quality forecasts are available to the public through the multiagency AirNow website (AirNow, 2021a) as well as state and local websites. Several western states have websites (“smoke blogs”) dedicated to providing the public with information on wildfire smoke impacts (Section A.4.1). The material delivered by these smoke blogs varies from state to state with the sites leveraging smoke and fire observations and forecast products from a variety of sources. National coverage is provided by the AirNow website, which uses ambient regulatory air quality monitoring data and calculates AQI values based on current measurements of six NAAQS pollutant indicators (particulate matter with a nominal aerodynamic diameter less than or equal to 10 µm [$PM_{10}$], $PM_{2.5}$, CO, nitrogen dioxide ($NO_2$), $O_3$, sulfur dioxide ($SO_2$) to inform the public of the current air quality conditions and what associated health effects may be of concern. AirNow also provides modeled forecasts for future air quality and links to numerous resources for understanding air quality during smoke episodes and protecting public health [e.g., U.S. EPA (2019e)]. The accuracy of the U.S. EPA AQI and the appropriateness of the associated AirNow public health messaging are a direct function of the underlying measured observational air quality data and spatial interpolation models.

The U.S. EPA and USFS have partnered to develop the AirNow Fire and Smoke Map [https://fire.airnow.gov/;AirNow (2021b)] through a pilot project that incorporates temporary monitors (Figure 4-1b) and beginning in 2020 air quality sensor data (Figure 4-1c), initially from PurpleAir $PM_{2.5}$ measurements (PurpleAir, 2021), to provide spatially improved AQI and associated public health messaging during wildfire season. The associated public health messaging on the site is augmented through direct access to the IWFAQRP daily Smoke Outlooks for specific incident impacted areas. PurpleAir and similar commercially available air quality sensors have just started to be evaluated under high smoke concentration conditions in laboratory and field studies. These evaluations demonstrate the sensors’ variable accuracies under different smoke impact conditions but highlight their potential for providing timely public health messaging during wildland fire smoke events after calibration of reported raw results (Landis et al., 2021; Delp and Singer, 2020; Holder et al., 2020; Mehadi et al., 2019). Remote sensing observations also provide the opportunity to visualize the downwind transport of wildland fire smoke and inform potential impacts on ambient air quality (Wu et al., 2018; Krstic and Henderson, 2015; Mei et al., 2012; Liu et al., 2009). The primary shortcoming of these satellite-based total air column measurements is there is no definitive way to know whether the observed plume is impacting surface air quality conditions or being transported aloft. Additionally, visible band measurements are only available during daylight hours, and plumes are only detectable at relatively high concentration. The emergence of a ground-based ceilometer network, the Unified Ceilometer Network (UCN); https://alg.umbc.edu/ucn/), through a collaboration between U.S. EPA, University of Maryland, Baltimore County (UMBC), National Aeronautics and Space Administration (NASA), and National Oceanic and Atmospheric Administration (NOAA) will provide three-dimensional aerosol backscatter profile measurements at numerous sites across the U.S. The ceilometer measurements will allow characterization of the smoke plume heights, including multiple layers, when smoke is transported over the sites.

This chapter summarizes current national regulatory ambient air quality measurement infrastructure, nonregulatory temporary incident response measurement capabilities, air quality sensor capabilities, and remote sensing products and their utility in estimating the impact of wildland fire smoke on air quality. Limiting exposure is the principal measure available to mitigate human health impacts of smoke, and real-time measurements of air quality are critical to providing actionable guidance to communities for minimizing population exposure. Air quality data from the current discrete federal, state, local, and tribal monitoring programs, remote sensing products, and ad hoc air quality sensor manufacturer's public web portal data are the basis for deterministic air quality model development and validation (CHAPTER 5) and wildland fire smoke exposure and health assessment research (CHAPTER 6). This chapter will also describe the current availability of air quality monitoring data, the relative accuracy of different types of monitoring instruments, public availability of measurement data, gaps in smoke monitoring capabilities, the challenges of ambient smoke monitoring, and provide recommendations to improve future ambient monitoring and data curation efforts for better characterization of the air quality impacts from wildland fire smoke.

## 4.2 Objectives of Air Quality Monitoring

### 4.2.1 Public Reporting of Air Quality through the Air Quality Index (AQI)

The Clean Air Act (CAA) requires U.S. EPA to protect public health and welfare by promulgating NAAQS for common harmful pollutants and establishing a uniform AQI for reporting of air quality for CO, $NO_2$, $O_3$, $PM_{2.5}$, $PM_{10}$, and $SO_2$. AQI values (0−500) are calculated individually for each of the five major air pollutants and are based on measured or forecast concentrations. The single AQI value reported on the multiagency AirNow represents the current highest individually calculated pollutant value (NowCast AQI) and is used to communicate how clean or polluted the air is, and guidance for planning outdoor activities (Table 4-1). During wildland fire smoke events $PM_{2.5}$ is typically the primary pollutant responsible for the elevated AQI values and the specific suggested intervention strategies to lower population $PM_{2.5}$ exposures to smoke and resulting negative health outcomes.

**Table 4-1 Understanding the U.S. Environmental Protection Agency Air Quality Index (AQI): An example for $PM_{2.5}$.**

| Level of Concern<br>Air quality conditions are: | AQI Color<br>As symbolized by this color | Value of Index<br>When the AQI is in this range: | $PM_{2.5}$ (µg/m$^3$)<br>With a 24-h concentration of: | $PM_{10}$ (µg/m$^3$)<br>With a 24-h concentration of: |
|---|---|---|---|---|
| Good | Green | 0−50 | 0.0−12.0 | 0−54 |
| Moderate | Yellow | 51−100 | 12.1−35.4 | 55−154 |
| Unhealthy for sensitive groups | Orange | 101−150 | 35.5−55.4 | 155−254 |
| Unhealthy | Red | 151−200 | 55.5−150.4 | 255−354 |
| Very unhealthy | Purple | 201−300 | 150.5−250.4 | 355−424 |
| Hazardous | Maroon | 301−400<br>401−500[a] | 250.5−350.4<br>350.5−500.4 | 425−504<br>505−604 |

µm/m$^3$ = micrograms per cubic meter; AQI = Air Quality Index; h = hour; PM = particulate matter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter greater than 2.5 µm and less than or equal to 10 µm; $PM_{10}$ = particulate matter with a nominal aerodynamic diameter less than or equal to 10 µm; SHL = significant harm level.

[a]An index value of 500 represents the SHL. SHL's are those ambient concentrations of air pollutants that present an imminent and substantial endangerment to public health or welfare, or to the environment, as established in 40 CFR 51.151 (U.S. EPA, 2001). For PM there is only a published SHL for $PM_{10}$.

State, local, and tribal agencies regularly monitor and report their air quality data to U.S. EPA for the calculation of AQI. However, most monitoring agency networks are designed around urbanized areas known as Core Based Statistical Areas (CBSAs). These networks are typically designed to evaluate the pollution exposure associated with anthropogenic pollution sources under meteorological conditions of pollution maxima as required by the CFR (U.S. EPA, 2015c). Air pollutant monitoring networks such as for $PM_{2.5}$ also include upwind, downwind, and transport sites for each state. State, local, and tribal agencies report all available data for calculation of the AQI as well as to understand transport into and out of their monitored jurisdictions. However, a major limitation of many state, local, and tribal agency networks is that the network design requirements associated with urbanized areas concentrate sites inside of major population centers. The focus on urbanized areas as well as the large geographical footprint of unmonitored rural areas often results in very limited or no monitors in areas adversely impacted by wildland fire smoke. Specifically, a recent U.S. Government Accountability Office report found that 2,120 of the 3,142 counties (67.5%) in the U.S. had no regulatory monitor (GAO, 2020).

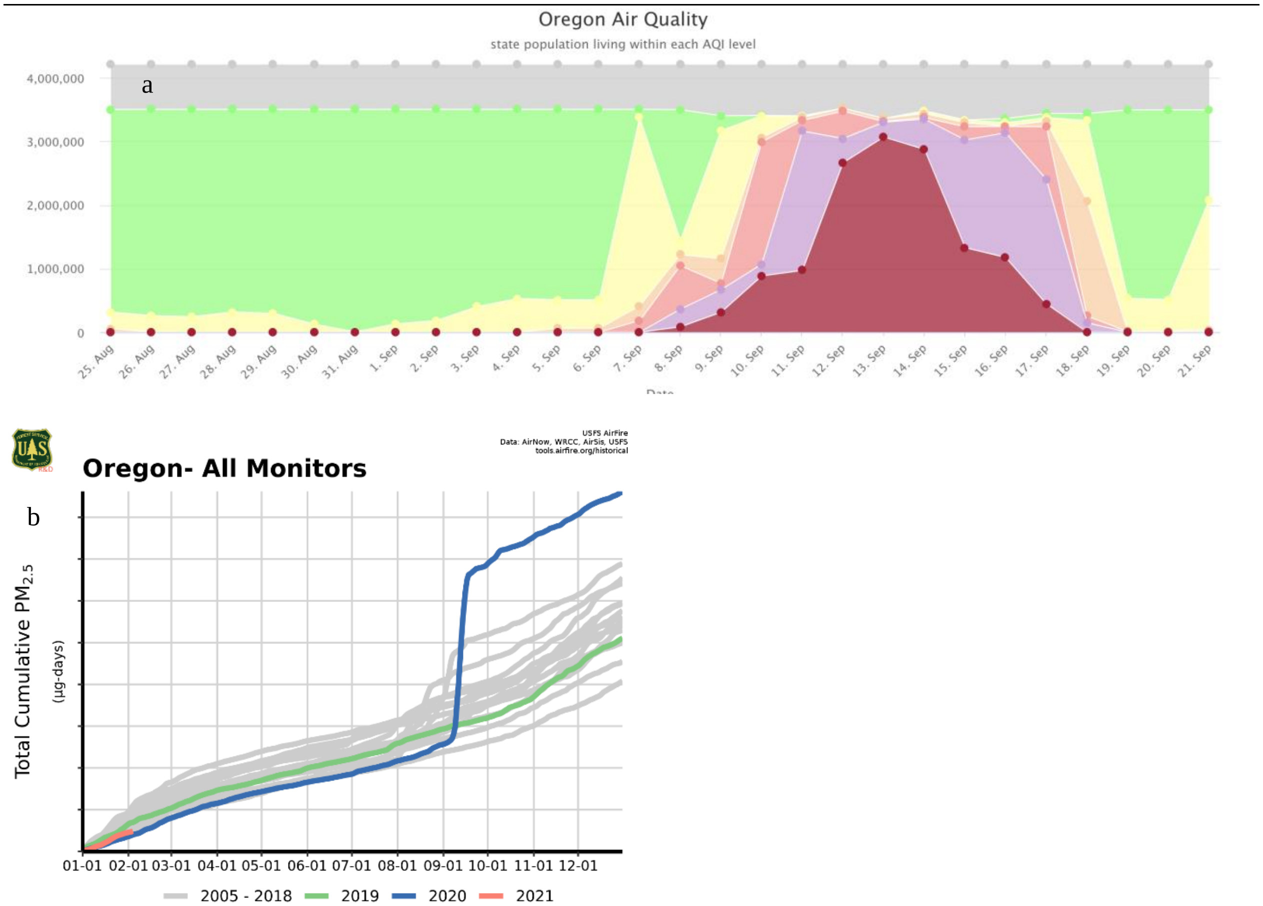
AQI values for $PM_{2.5}$ and $O_3$ presented on the AirNow website, App, or widget that are entitled "current air quality" are calculated using the U.S. EPA NowCast algorithms. The full AQI is based on averaging times used for the NAAQS: 24-hour local midnight to midnight average for $PM_{2.5}$ and $PM_{10}$; max 8-hour avg for CO and $O_3$; and max 1-hour avg for $NO_2$ and $SO_2$. The NowCast algorithm is complex, but is designed to approximate the full AQI, but to also be more responsive to recent data trends and to be calculable after each new hour's data (U.S. EPA, 2020d). The NowCast algorithms dynamically scale the duration of past hourly monitoring data used to calculate the Current AQI based on the observed temporal trend of ambient concentrations, using longer time averages during stable concentrations and shorter time averages when air quality is changing rapidly. In practice they often approximate a 3-hour running average. The hourly updated NowCast $PM_{2.5}$ and $O_3$ AQI values are useful during wildland fire events when downwind ambient air quality can change abruptly but do not necessarily reflect up-to-the-minute current conditions.

### 4.2.2 Analyzing Air Quality Trends

In addition to directly informing AQI, regulatory network air quality data collected from fixed state, local, and tribal monitoring stations with at least several years of data allow for the characterization of air quality trends and provides context for understanding wildland fire smoke conditions. U.S. EPA maintains an annual air trends report in the form of an interactive web application [e.g.,. https://gispub.epa.gov/air/trendsreport/2020/; U.S. EPA (2020g)]. The online report features a suite of visualization tools that allow the user to:

- Learn about air pollution and how it can affect our health and environment.
- Compare key air emissions to gross domestic product, vehicle miles traveled, population, and energy consumption back to 1970.
- Take a closer look at how the number of days with unhealthy air has dropped since 2000 in 35 major U.S. cities.
- Explore how air quality and emissions have changed over time for each of the common air pollutants.
- Check out air trends where you live.

Information about long-term air quality trends can be useful in determining the extent to which air quality management strategies are helping reduce concentrations of pollutants to the levels specified by the NAAQS. Online resources are also available that present daily trends in air quality during wildland fire events that can be used to estimate daily (Figure 4-2a) and year-to-date (Figure 4-2b) population exposure [https://tools.airfire.org; regional air quality and historical tools; USFS (2021b)]. The AirFire resource can be used to contextualize the current air quality conditions during large wildland fire events and the dramatic impact on population $PM_{2.5}$ exposure like that from a September 2020 wildfire event on the state of Oregon presented in Figure 4-2b.




AQI = Air Quality Index; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; USFS = U.S. Forest Service; WRCC = Western Regional Climate Center.

Colors shown in Figure 4-2a are U.S. EPA AQI categories (Table 4-1) and grey indicates no data.

Source: https://covid.airfire.org/tracking/. IWFAQRP (2021); site uses U.S. EPA regulatory monitor data and an analysis of LANDSCAN population data within 20 km of each monitoring site.

**Figure 4-2 Tracking of Air Quality Index (AQI) in Oregon during the 2020 wildfire season (a) and the cumulative annual Oregon population exposure to $PM_{2.5}$ (b) showing the clear impact of wildland fire events.**

### 4.2.3 Informing Fire Management

Smoke from wildland fires can impact the health and safety of fire personnel and the public, interfere with fire suppression operations and transportation, and disrupt local economies (USFS, 2020a). Because of the scale of these impacts, such as those seen during the 2020 western U.S. wildfire season, these impacts can become the focus of fire management, air quality regulators, and public health officials. The USFS led the development of the IWFAQRP to address the air quality impacts of wildfires on the American public. IWFAQRP uses emergency deployable air quality monitoring equipment, state-of-theart wildland fire smoke dispersion models, and ARAs for dispatch to ongoing wildfires to develop and publicly disseminate smoke impact information (USFS, 2020a). ARAs are technical specialists that deploy nationwide to large wildfires to assist with understanding and predicting smoke impacts on local communities and fire personnel. They work on Incident Management Teams with their public information, fire behavior, and fire weather specialists as well as coordinate with local emergency response, air regulatory, and public health agencies to provide timely smoke outlooks that address the public health risks and concerns from smoke (USFS, 2020a). In areas without an existing $PM_{2.5}$ monitor, ARAs deploy temporary PM monitors to provide real-time information on air quality to assist local officials and communities make informed decisions to minimize their exposure to smoke. ARAs are also a point of contact for the public and commonly present smoke information at public meetings and address smoke-related concerns of local citizens.

Smoke impacts from prescribed fires also present significant challenges to land management agencies. Prescribed fire is an important tool for achieving key management objectives such as ecosystem restoration and maintenance and hazardous fuel reduction. Smoke management concerns are among the top impediments to prescribed burning [Melvin (2018, 2015); see CHAPTER 3]. While nuisance smoke is the most common smoke issue, prescribed fires can subject local communities and sensitive populations to unhealthy levels of $PM_{2.5}$ (Melvin, 2018, 2015). Prescribed fire smoke can also endanger public safety by reducing visibility on roadways leading to serious and/or fatal traffic accidents (Bartolome et al., 2019; Ashley et al., 2015). Additionally, unlike wildfires, prescribed fires are considered a controllable emission source and the resultant smoke can trigger a regulatory violation of NAAQS. However, the 2016 Exceptional Events Rule states that prescribed fire on wildland can be a human-caused event eligible for treatment as an exceptional event, and properly managed prescribed fires are generally less likely than wildfires to cause or contribute to an exceedance or a violation of the NAAQS (U.S. EPA, 2019d). In instances where smoke from a prescribed fire leads to an exceedance or violation of a NAAQS, and all rule criteria are satisfied, air agencies or federal land managers can prepare an exceptional events demonstration and request the event-influenced data to be excluded from the data set used for certain regulatory determinations. To help mitigate these deleterious smoke impacts and obtain observational data to improve smoke management techniques and tools, land management agencies and atmospheric researchers have increasingly begun to deploy temporary smoke monitors as part of operational prescribed burns (Pearson, 2021).

### 4.2.4 Quantifying the Impact of Wildland Fires on Air Quality

One of the key objectives of the U.S. EPA regulatory air monitoring program is quantifying specific anthropogenic source impacts on NAAQS pollutant concentrations. However, there are no existing national monitoring programs specifically designed to evaluate air pollutant impacts from wildfires or prescribed fire programs even though the U.S. EPA National Emissions Inventory (NEI) has reported wildland fires contribute a substantial amount to total national annual CO (30−43%) and $PM_{2.5}$

(32−44%) emissions from 2011−2017 (U.S. EPA, 2021b). However, it remains unclear how emissions of these pollutants from wildland fires translates to overall contributions to annual ambient concentrations. To date, U.S. EPA has not undertaken a national measurement-based integrated assessment into the impact of wildland fire emissions on (1) ambient air quality, (2) regulatory NAAQS compliance, or (3) negative human health outcomes. There are numerous local/regional assessments in the scientific literature that document the deleterious changes on ambient air quality, human exposures, and human health outcomes related to specific wildfire events (Stowell et al., 2019; Landis et al., 2017; Reid et al., 2016; Cisneros et al., 2012; Rappold et al., 2011). Incremental progress in the examination of the local/regional impact of wildland fire smoke on ambient air quality, human exposure, and human health effects is being made (Johnson et al., 2020). However, in the absence of a national measurement-based assessment the full impact of wildfire smoke remains largely unknown on a national scale, particularly at population centers that are often distant from wildfire events.

## 4.3 Ambient Air Quality Monitoring Capabilities

### 4.3.1 Overview

The fundamental understanding of wildland fire source emission estimates, the impacts of smoke on air quality, human exposures and health outcomes, and the ability to develop and validate predictive deterministic air quality models, are predicated on accurate measurements of air pollutants in smoke. While there are no U.S. EPA national air quality monitoring networks focused on wildland fire smoke, there are several discrete federal, state, local, and tribal monitoring programs and ad hoc air quality sensor networks that provide critical observational air quality data during wildland fire events. This section summarizes current national regulatory ambient air quality measurement infrastructure, nonregulatory temporary incident response measurement capabilities, air quality sensor capabilities, and remote-sensing products and their utility in estimating the impact of wildland fire smoke on air quality.

### 4.3.2 U.S. EPA Routine Regulatory Monitoring Networks

U.S. EPA has established NAAQS for the criteria pollutants and maintains multiple national regulatory air pollution monitoring networks as required by the CAA that are set forth in Title 40, Part 50 of the Code of Federal Regulations (U.S. EPA, 2016). Each monitoring network has associated regulatory requirements and policy objectives that dictate decisions on the location of and pollutants measured at each site. In addition to reporting the AQI in large population centers, key monitoring objectives include NAAQS compliance, trend analysis, quantifying specific source impacts, and improving the performance of air quality forecast models. National monitoring of air quality is accomplished through a partnership of U.S. EPA delegated federal, regional, state, city, and tribal stakeholder organizations. U.S. EPA regulatory monitoring is carried out as part of a national network of approximately 4,400 monitoring sites, called the State and Local Air Monitoring Stations (SLAMS). The air quality data obtained from these sites are reported to U.S. EPA's Air Quality System (AQS) database, along with other information, and are used for determining compliance with the NAAQS, assessing effectiveness of State Implementation Plans (SIPs) in addressing NAAQS nonattainment areas, characterizing local, state, and national air quality status and trends, and associating health and environmental damage with air quality levels/concentrations.

To assure the accuracy, integrity, and uniformity of the SLAMS air quality monitoring data collected, the U.S. EPA has established one or more FRM for measuring each of the six criteria pollutants. These FRMs are set forth in appendices to 40 CFR Part 50 and specify a measurement technique to be implemented in commercially produced monitoring instruments (U.S. EPA, 2020f, h, i, j, k, 2011a, b, c). These monitoring instruments must be shown to meet specific performance requirements in addition to other requirements detailed in the U.S. EPA regulations at 40 CFR Part 53 (U.S. EPA, 2019a), in which case the instrument may be designated by the U.S. EPA as an FRM analyzer. To encourage innovation and development of new air quality monitoring methods, the U.S. EPA has also provided for FEMs. An FEM is not constrained to the specific measurement technique of the corresponding FRM. However, an FEM must meet the same or similar performance requirements as specified for the corresponding FRM, and in addition, it must show a high degree of comparability to collocated FRM measurements at one or more field testing sites under typical ambient conditions. These FEM requirements are also detailed in 40 CFR Part 53 (U.S. EPA, 2019a), and a monitor that is shown to meet all applicable requirements may be designated by the U.S. EPA as an FEM monitor. A current listing of all designated FRMs and FEMs as of December 2020 can be found at https://www.epa.gov/sites/production/files/2019-08/documents/designated_reference_and-equivalent_methods.pdf (U.S. EPA, 2020e).

The siting criteria and regulatory monitoring methodologies are briefly described here and a detailed discussion of specific air pollution networks, criteria air pollutants measured, and measurement methods are provided in Section A.4.2 ($PM_{2.5}$ Mass Monitoring), Section A.4.3 ($PM_{2.5}$ Speciation Monitoring), and Section A.4.4 (Criteria Gas Monitoring). The U.S. EPA $PM_{2.5}$ monitoring program is the largest component of the national monitoring infrastructure and $PM_{2.5}$ monitors are mostly sited in urban areas at the neighborhood scale as defined in 40 CFR Appendix D to Part 58 (U.S. EPA, 2015a, b), where typical $PM_{2.5}$ concentrations are reasonably homogeneous throughout an entire subregion in the absence of wildland fire smoke. There are four main components of the U.S. EPA $PM_{2.5}$ monitoring program: 24-hour integrated filter-based FRM samplers, continuous FEM mass instrument measurements reported as 1-hour concentrations, continuous non-FEM mass instrument measurements reported as 1-hour concentrations, and 24-hour integrated filter-based Chemical Speciation Network (CSN) samplers. Continuous $PM_{2.5}$ FEM and criteria gas FRM/FEM (Table A.4-1) real-time data support NAAQS compliance and is integrated with non-FEM continuous $PM_{2.5}$ data to support public AQI communication and air quality smoke forecasting on AirNow (AirNow, 2021a). The top three states using the non-FEM continuous $PM_{2.5}$ instruments for AQI reporting are Washington (n = 47), Oregon (n = 45), and California (n = 43) primarily to communicate air quality impacts from wildland fire smoke.

### 4.3.3 Temporary/Incident Response Measurements

The IWFAQRP provides significant incident response smoke monitoring capabilities by maintaining a cache of smoke monitoring equipment for nationwide deployment by their ARA personnel. The IWFAQRP smoke monitor cache consists of ~40 Met One Instruments (Grants Pass, OR) E-SAMPLER and E-BAM nonregulatory $PM_{2.5}$ samplers (USFS, 2020a). These $PM_{2.5}$ samplers are available upon request to land management agency administrators and incident management teams for monitoring wildfires and to federal land managers conducting prescribed burns. The monitors are typically used by ARAs supporting wildfire incident management teams. The ARA will often consult with local land managers, air quality regulatory agencies, and public health officials for guidance on positioning temporary smoke monitors. When siting monitors, ARAs attempt to meet the same siting criteria as used for regulatory FRM/FEM monitors like avoiding interferences from other emission sources or physical barriers that may obstruct air flow around the sampler (U.S. EPA, 2012). Deployment of either the E-BAM or E-SAMPLER requires a land line power hookup, but since these monitors are intended to inform communities, this infrastructure requirement is not typically an issue as they are often deployed at fire stations, schools, or other municipal buildings. The E-BAM and E-SAMPLER both upload their measurement data by satellite to a cloud-based data acquisition system where it is reported on an hourly basis. The data must then pass a quality assurance (QA) check before being publicly distributed through the www.airfire.org or the www.fire.airnow.gov websites (see Section 4.4.3).

Beyond the national smoke monitoring resources offered by IWFAQRP, jurisdictions within federal agencies (e.g., USFS Regions), states, and tribal agencies also maintain and deploy PM samplers for monitoring smoke impacts from wildfires and prescribed burns. The PM samplers used include ThermoFisher Scientific (Franklin, MA) DataRAM pDR-1500 and Met One Instruments BAM-1020, E-BAM, and E-SAMPLER systems (USFS, 2020b). Remote telemetry and satellite data transmission are used to gather and present the raw data in “near-real-time” (USFS, 2020b). These data are also collected and integrated into the www.fire.airnow.gov websites (see Section 4.4.3). Several states have programs to monitor smoke from wildland fires. The most extensive program is in California, where the California Air Resources Board (CARB) and local air districts have >100 E-BAM samplers available for deployment to monitor smoke impacts (Pearson, 2021). The CARB program initially targeted wildfires but was expanded in response to state legislation (California SB-1260, 2018) which sought to increase hazardous fuels reduction and included funding for prescribed fire smoke monitoring. Other states with monitoring efforts for wildfire and prescribed fire include Alaska, Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, and Washington as well as some tribes (Section A.4.1). Even with the deployment of temporary PM monitors supplied by federal, tribal, state, or local agencies, gaps in air quality observations often persist, especially in lower population foothill and mountain communities. To address monitoring gaps, ARAs began deploying PM sensors (Purple Air) in 2020 to estimate the air quality in communities that previously would have gone without monitoring. Likewise, states and local agencies are augmenting existing monitoring networks with air quality sensors. In 2018, CARB initiated a pilot program that distributed several hundred PM sensors to augment existing air quality monitoring networks and capabilities (Pearson, 2021).

Historically, smoke monitoring for wildfire response has relied on existing and temporarily deployed stationary monitors to provide air quality information to incident command and state/local public health officials. The relatively small number of local monitors, the dynamic nature of smoke emissions and transport, and the dispersed nature of firefighting personnel and downwind communities make predicting exposures challenging. Mobile monitoring capabilities are another strategic approach to measure and communicate real-time smoke information. Personal monitoring of firefighters, vehicle mounted instruments, and airborne drones are all viable mobile monitoring platforms. These approaches have been used in focused research studies (Apte et al., 2017; Navarro et al., 2016; Villa et al., 2016) but not for routine operations. Research into both built-for-purpose and commercially available small-form-factor air quality measurement systems have been reported by Landis et al. (2021) and Holder et al. (2020), respectively; and others are working on continuous reading mobile air quality platforms (2B Tech, 2021; Mui et al., 2021; Apte et al., 2017).

With exception of the BAM-1020, monitors used by federal, state, local, and tribal agencies for temporary smoke monitoring are not expected to be U.S. EPA designated FEM monitors. Across all agencies the most frequently deployed monitors are E-BAM and E-SAMPLERS. The performance of both samplers in measuring $PM_{2.5}$ in fresh smoke has been evaluated in limited laboratory testing which indicates high correlation ($r^2 > 0.9$) and relatively low bias range for the E-BAM (1−21%) and E-SAMPLERS (8−18%) compared to reference FRM/FEM monitors across concentration ranges of 20−1,700 μg/m$^3$ (Mehadi et al., 2019; Trent, 2006, 2003). However, it is unclear how the samplers perform across the natural range of smoke properties (chemical composition, size distribution) and how performance may vary over extended periods of sampling in smoke impacted environments. Additionally, federal interagency smoke monitor inventories also include DataRAM monitors, and laboratory evaluation of these monitors indicates they overestimate $PM_{2.5}$ in smoke by a factor of ~2 (Trent, 2003).

### 4.3.4 Sensors

Over the last decade there has been rapid development of miniaturized, user-friendly air quality sensor systems (Karagulian et al., 2019; Malings et al., 2019; Baron and Saffell, 2017; Williams et al., 2015). Significant advancements in internal gas and PM sensor components, compact microprocessors, power supply/management, wireless data telemetry, advanced statistical data fusion/analysis, real-time sensor calibration, and graphical data interfaces hint at the future potential of accurate small form factor integrated air quality sensor systems. This technology is being developed for a variety of potential applications, including human exposure assessment (Morawska et al., 2018), industrial emissions (Thoma et al., 2016), local source impact estimation (Feinberg et al., 2019), and to increase the spatial density of outdoor monitoring networks (Bart et al., 2014; Mead et al., 2013). Some manufacturers of air quality sensor systems have built cloud-data systems and public websites to host measurement data and allow public access (2B Tech, 2021; Kunak, 2021; PurpleAir, 2021). The large number of installed sensors and centralized data hosting capabilities of PurpleAir (Draper, UT) led the U.S. EPA and USFS to launch a pilot project to provide data from air quality sensors calibrated with U.S. EPA's correction equation (Barkjohn et al., 2020) and the derived AQI and NowCast on the AirNow Fire and Smoke Map. The goal of the pilot project was to provide additional AQI ($PM_{2.5}$ only) information during wildfires in those areas not adequately served by regulatory monitoring sites (AirNow, 2021a).

However, the reliability, accuracy, stability, and longevity of many types of air quality sensors under smoke conditions is largely unknown. Routine performance testing of many air quality sensors, to date, has been mostly limited to typical ambient conditions (Collier-Oxandale et al., 2020; Zamora et al., 2019; Feinberg et al., 2018; Jiao et al., 2016; Williams et al., 2015), with more limited assessment of certain technologies at higher ambient concentrations (Johnson et al., 2018; Zheng et al., 2018). These previously published findings have indicated, in some cases, high correlation between collocated sensors and FRM/FEM reference monitors; however, there are also many sensor test results that exhibit measurement artifacts (Hossain et al., 2016; Lin et al., 2015; Spinelle et al., 2015; Mead et al., 2013), inconsistency among identical sensors (Sayahi et al., 2019; Castell et al., 2016; Williams et al., 2015), drift over time (Sayahi et al., 2019; Feinberg et al., 2018; Artursson et al., 2000), sensitivity to environmental conditions [e.g., temperature, relative humidity; Wei et al. (2018); Cross et al. (2017)], and limitations to upper limit measurement capabilities (Zou et al., 2020; Schweizer et al., 2016). U.S. EPA has endeavored to improve the reliability, consistency, and accuracy of air quality sensor data by regularly engaging academia, industry, nonprofit groups, community-based organizations, and regulatory agencies to develop recommendations, performance targets, and best practices (Duvall et al., 2021a, b; Williams et al., 2019; Clements et al., 2017). U.S. EPA has also created an online Air Sensor Toolbox (U.S. EPA, 2021a) as a clearinghouse for information on the use of air quality sensors. The U.S. EPA Air Sensor Toolbox aims to improve the operation, data collection, and quality assurance of air sensor data by providing resources such as the Air Sensors Guidebook, Standard Operating Procedures (SOPs) for sensors, Sensor Performance Targets and Test Protocols, Sensor Collocation Guide, Sensor Evaluation Reports, Quality Assurance Handbook and Guidance Documents for Citizen Science Projects, and air sensor loan opportunities to enable the public to learn about air quality in their communities (U.S. EPA, 2020b).

More recently U.S. EPA partnered with other U.S. federal agencies (Centers for Disease Control and Prevention (CDC), NASA, National Park Service (NPS), NOAA, USFS) to sponsor the Wildland Fire Sensor Challenge to advance wildland fire air measurement technology to be easier to deploy, suitable to use for high concentration events, and durable to withstand difficult field conditions, with the ability to report high time resolution data continuously and wirelessly (Landis et al., 2021). The Wildland

Fire Sensor Challenge encouraged innovation worldwide to develop sensor prototypes capable of measuring $PM_{2.5}$, CO, carbon dioxide ($CO_2$), and $O_3$ during wildfire episodes. The raw $PM_{2.5}$ sensor accuracies of the three winners ranged from ~22−32%, while smoke specific U.S. EPA regression calibrations improved the accuracies to ~75−83% demonstrating the potential of these systems in providing reasonable accuracies over conditions that are typical during wildland fire events (Landis et al., 2021). Select commercially available $PM_{2.5}$ sensors have also been evaluated versus collocated FEM measurements under smoke conditions that highlight their potential for providing useful public health messaging during wildland fire smoke events (Delp and Singer, 2020; Holder et al., 2020; Mehadi et al., 2019). These research studies like the Wildland Fire Sensor Challenge have shown that raw $PM_{2.5}$ sensor data requires post-processing using smoke specific calibration functions to account for differences in aerosol chemistry, particle size distribution, aerosol density, and optical properties. The range of smoke specific calibration correction factors are summarized in Table A.4-2 and show a broad range of responses depending on specific fire conditions and reference instruments used. As more information is gathered on the performance and calibration of air quality sensors in wildland fire smoke, the utility of their reported air quality measurements for informing public health messaging will improve.

### 4.3.5 Remote Sensing/Satellite Data

Remote sensing is the science of acquiring information about the Earth's surface or atmosphere without actually being in contact with it and requires a source of reflected, emitted, or absorbed and re-emitted energy which interacts with the geophysical parameter being measured, such as aerosols (e.g., $PM_{2.5}$) in the atmosphere. As a result, remote sensing allows for the estimation of wildfire smoke impacts in areas of the country that lack other sources of ground-based observational data. The two types of remote sensing are referred to as passive and active. Passive remote sensing uses the sun as the energy source, where the solar radiation is reflected by the Earth's surface or scattered in the atmosphere for visible wavelengths or absorbed and then re-emitted from the earth surfaces for thermal infrared wavelengths. Because measurements made in the visible wavelengths require reflected solar radiation, they can only be conducted during daylight hours. Active remote sensing techniques require their own energy source, where the emitted radiation is directed at the target of interest and reflected back to the instrument. In active remote sensing, lasers often provide this energy source, and the pulsing energy can provide information on 3-dimensional structure of the geophysical variable being measured; this technique is called Light Detection and Ranging (LiDAR).

#### 4.3.5.1 Satellite Measurements

Satellite observations from both low earth and geostationary orbit have become an important set of measurements for monitoring air pollutant abundances and transport across large spatial scales. Instruments aboard low-earth-orbit satellites most often provide once-a-day observations over the region of interest and with large swaths provide global coverage every day. Geostationary satellites are in fixed-orbit position relative to the earth and used to observe phenomena which require high-temporal resolution observations, such as severe weather and disasters, such as wildland fires. Most satellite instruments used to provide information on air quality are passive remote sensing instruments and span wavelengths in the ultraviolet-visible (UV/VIS) range or the thermal infrared. The visible wavelengths are used to provide true color imagery which can be used to identify smoke from wildland fires in a cloud-free scene. More quantitative measurements involve the measure of backscatter radiances in the UV/VIS or thermal infrared emission through the atmosphere to provide a derived geophysical column measurement dependent on physics-based retrieval algorithms (Martin, 2008). Over the past two decades, satellite column measurements are increasingly being used to provide near-surface information on pollutants such as $PM_{2.5}$, $O_3$, $NO_2$, $SO_2$, CO, and formaldehyde ($CH_2O$). Polarimetric, multispectral, multidirectional, and active remote sensing observations bring information on the aerosol amount, size, type, and vertical distributions of column abundances of the geophysical parameter of interest.

One of the major challenges of passive remote measurements from satellites is resolving the vertical distribution of the parameter of interest, and in some cases the sensitivity of the satellite measurement to the lowermost atmosphere, which is the region with substantial variability and the most relevant for gaining an understanding of ambient air quality and subsequent public health impacts (Martin, 2008). Nevertheless, it is well documented that satellite-derived geophysical parameters of column integrated abundances such as aerosol optical depth (AOD) can be used to constrain estimates of near-surface pollution concentration, especially when used in combination with model (chemical transport or statistical)-based predictions, and provide valuable information on the horizontal distribution of the pollutant burdens because of the satellite instrument synoptic field-of-view. Smoke plume height characteristics from the Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm (Lyapustin et al., 2019), which is based on 11-µm absorption of fire-emitted gases in the plume, have shown potential for improving surface $PM_{2.5}$ concentration estimates derived from AOD (Cheeseman et al., 2020). LiDARs aboard satellites have a unique capability of resolving the vertical distribution of aerosol in the atmosphere and can make measurement during the day and night (Winker et al., 2010) but have very limited spatial coverage to capture wildland fire plumes (Raffuse et al., 2012). TROPOspheric Monitoring Instrument (TROPOMI) provides an aerosol height index which is a developing data product (Griffin et al., 2020) and offers the ability to diagnose the aerosol plume height to help assess if the majority of aerosol seen by satellite is within the boundary layer or being transported aloft.

##### 4.3.5.1.1 Correct Reflectance True Color Imagery—Smoke Plume Identification and Tracking

Satellite-corrected reflectance from visible wavelengths, also referred to as true color imagery, from both geostationary and low earth (polar) orbiting satellite instruments is one of the basic satellite data products used to identify the spatial extent of smoke plumes and transport from wildland fires. In addition to providing access to true color images from Geostationary Operational Environmental Satellites (GOES), satellite analysts at NOAA develop a daily smoke analysis over the contiguous U.S. and adjacent area of Canada through their Hazard Mapping System (HMS) Fire and Smoke Product website (https://www.ospo.noaa.gov/Products/land/hms.html#maps). The HMS products use multiple data inputs to create a digitized data product displaying the extent of visible smoke and a qualitative classification on the density of the smoke as low, medium, or high based on visible opacity determined by the analysts (NOAA, 2020). In combination with surface observation of pollutants or visibility these imagery-based data products can help identify areas with air quality impacts from wildland fires, but alone these products provide no information on air quality at the surface.

###### 4.3.5.1.2 Satellite (Geophysical) Composition Observations

AOD is an integrated measure of extinction through the atmosphere that is the derived geophysical variable from satellite instruments most relevant to $PM_{2.5}$ and $PM_{10}$ mass concentrations. Both operational and research algorithms are used to generate AOD from passive satellite sensors such as MODIS, Multiangle Imaging Spectroradiometer (MISR), Visual Infrared Imaging Radiometer Suite (VIIRS), and the GOES Advanced Baseline Imager (ABI). Deriving near-surface PM concentrations from AOD values is difficult. The challenges in deriving PM concentrations from AOD values are related to uncertainties in the microphysical (intrinsic) properties of the particles, their size distribution, aerosol type, and hygroscopic state, as well as key extrinsic properties, such the vertical profile distribution (Hoff and Christopher, 2009). Few measurements studies have examined the uncertainties associated with the use of AOD measurements to estimate ground-based $PM_{2.5}$. Early results from the NASA DISCOVER-AQ mission over the urban Baltimore region (Crumeyrolle et al., 2014) found accurate quantification of the aerosol mixed layer height is critical for predicting $PM_{2.5}$ concentrations, with aerosol type variability being of lesser importance. In addition, the results indicate the presence of aerosol layers above the boundary layer introduced significant uncertainties in surface $PM_{2.5}$ concentrations estimates when using a column-integrated AOD measurements, and that active remote-sensing techniques such as LiDARs can provide a characterization of aerosol layers to improve upon the $PM_{2.5}$ estimates. The transport of smoke plumes can often result is stratified aerosol layers, including aerosol layers above the boundary layer, so proper characterization of such aerosol layer structure remains a critical variable in use of satellite AOD to predict surface $PM_{2.5}$ concentrations.

Geophysical retrievals of trace gas column abundance from satellite have seen great improvements in spatial resolution over the past several decades with European Space Agency (ESA) Sentinel 5 Precursor TROPOMI launched in 2017 now producing global daily $NO_2$ observations at a resolution (7 × 3.5 km) consistent with chemical transport modeling used for wildland fire air quality forecasting. In addition to $NO_2$, TROPOMIs standard trace gas data products include column abundances of $CH_2O$, $SO_2$, CO, and methane at varying spatial resolutions (Levelt et al., 2006). The NASA

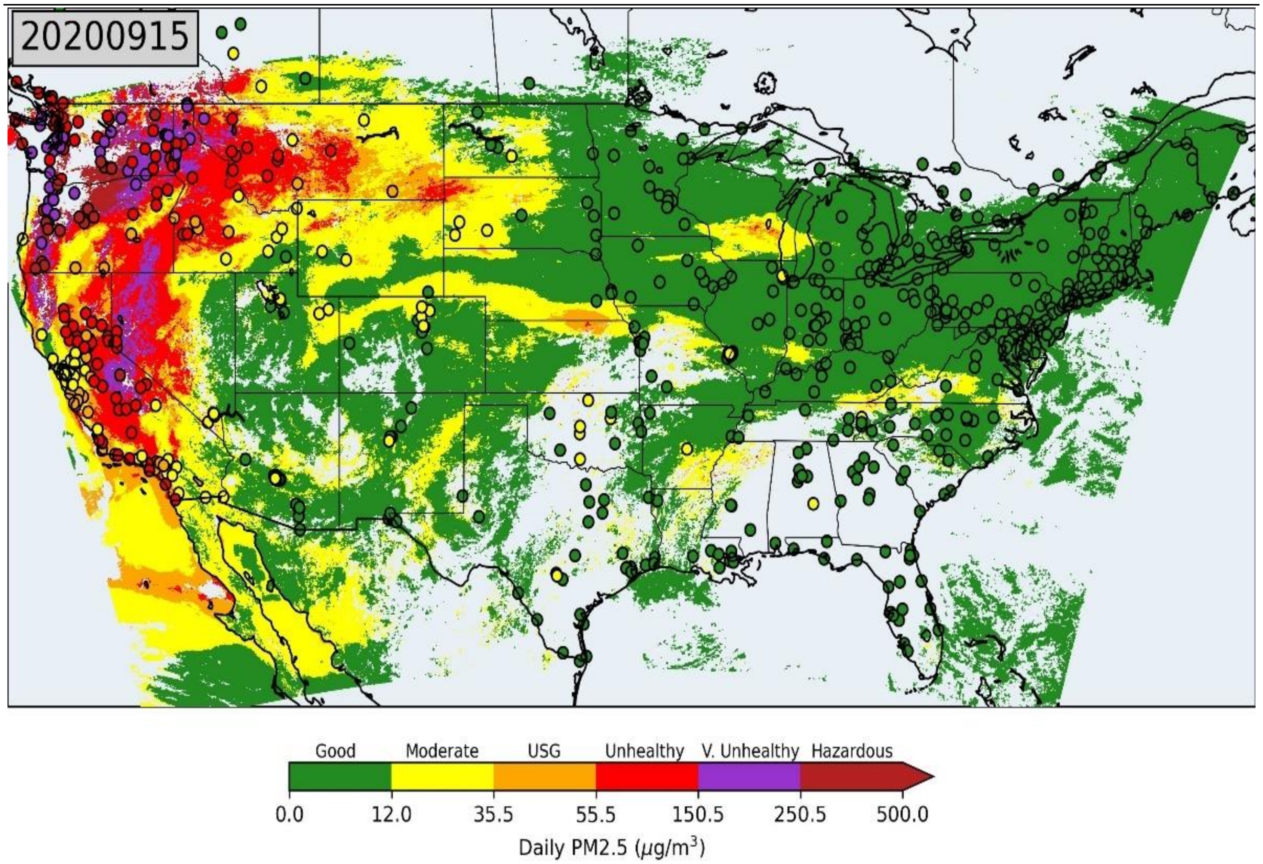
Tropospheric Emissions: Monitoring Pollution (TEMPO) mission, scheduled to launch in mid-2022 into a geostationary orbit, will provide hourly observations of $NO_2$ and $O_3$, across the North American continent during daytime (Zoogman et al., 2017).

Because there are significant portions of the U.S. that have no continuous surface monitors, a very active stream of research developed in the early 2000s focused on the use of column abundances of the aerosol (AOD) and trace gas satellite data products to aid in the predictions of pollutant surface concentrations. Over the past 20 years many research groups have developed a multitude of methods to model surface $PM_{2.5}$ concentrations using AOD from numerous satellites as discussed in a review by Chu et al. (2016) with a primary focus on estimates of annual $PM_{2.5}$ concentrations. Some research groups have continued to improve upon the methods over time as inputs in the methods have improved (Hammer et al., 2020), including estimates of PM chemical composition (van Donkelaar et al., 2019) and have made their data sets available for public use (Atmospheric Composition Analysis Group, 2021). Similar research efforts combine chemical transport model and $NO_2$ column abundances to infer surface concentrations (Cooper et al., 2020). Most of these research efforts focus on predictions of annual means for these pollutants versus daily predictions of surface concentrations. For example, Alvarado et al. (2020) has recently demonstrated the transport and tracking of several trace gases associated with wildland fires in western Canada.

Useful and actionable information for wildland fire pollutants requires daily predictions of surface pollutants, such as $PM_{2.5}$, or more temporally resolved information because of the diurnal nature of wildland fire emissions and meteorological transport patterns (Baker et al., 2019). Methods focused on the use of satellite data to aid in daily pollutant surface predictions during wildland fires have been demonstrated on a very limited basis through a case-study approach, and include simple regression analysis (Raffuse et al., 2013), machine learning techniques (Reid et al., 2015), and generalized geographically weighted regression models (Gupta et al., 2018; Gupta and Christopher, 2009), all with moderate success. Resolving the apportionment of AOD impacting the surface concentrations is complicated because of long-range and high-altitude transport of aerosols which often occurs for wildland fire events. While not associated with surface $PM_{2.5}$ predictions for wildland fires, Jin et al. (2019) used a geophysical approach to estimate daily surface $PM_{2.5}$ concentrations and conducted a detailed assessment of uncertainties using this approach, estimating uncertainties in the modeled $PM_{2.5}$/AOD led to an error of 1 $\mu g/m^3$ in daily $PM_{2.5}$ predictions, and while satellite AOD uncertainties produced errors of 8 $\mu g/m^3$. However, none of these efforts provide an ongoing source of data.

The U.S. EPA AirNow Program application called the AirNow Satellite Data Processor (ASDP) (Pasch et al., 2013) integrates AOD from the MODIS instruments (Terra and Aqua) with a focus on improving the accuracy of daily ground-level $PM_{2.5}$ concentrations. The ASDP approach based to provide $PM_{2.5}$ predictions uses climatological scaling factors (van Donkelaar et al., 2019) from GEOS-Chem. The NOAA Aerosol Watch provides access to a variety of relevant GEOS (16 and 17) and VIIRS (S-NPP and NOAA-20) data products, including true color imagery and AOD retrievals which can be overlaid with

AirNow $PM_{2.5}$ data to help assess if the satellite data and surface concentrations are spatially correlated in time and space which is an indication that the smoke extent observed by the satellite is at or near the surface impacting ground level air quality. Figure 4-3 is a result of recent efforts by NOAA Aerosol Watch to product an operational daily satellite derived $PM_{2.5}$ product for September 15, 2020 during the Oregon wildland fires. This approach aggregates VIIRS AOD from two polar orbiting satellites, S-NPP and NOAA-20, and applies a regression algorithm from available surface $PM_{2.5}$ data to produce a daily satellite derived $PM_{2.5}$ field.




$PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Note: This figure captures spatial extent of poor air quality associated with several large western wildland fire complexes over the western U.S. Closed circles in the plot represent surface monitors of $PM_{2.5}$.

Image Source: Shobha Kondragunta (NOAA/NESIDS).

**Figure 4-3 Image of surface Air Quality Index (AQI) for $PM_{2.5}$ from U.S. EPA AirNow over plotted with Air Quality Index (AQI) for $PM_{2.5}$ derived from National Oceanic and Atmosphere Administration (NOAA) aerosol optical depth from Visible Infrared Imaging Radiometer Suite (VIIRS) instruments (Soumi-NPP and NOAA-20 satellites) for September 15, 2020.**

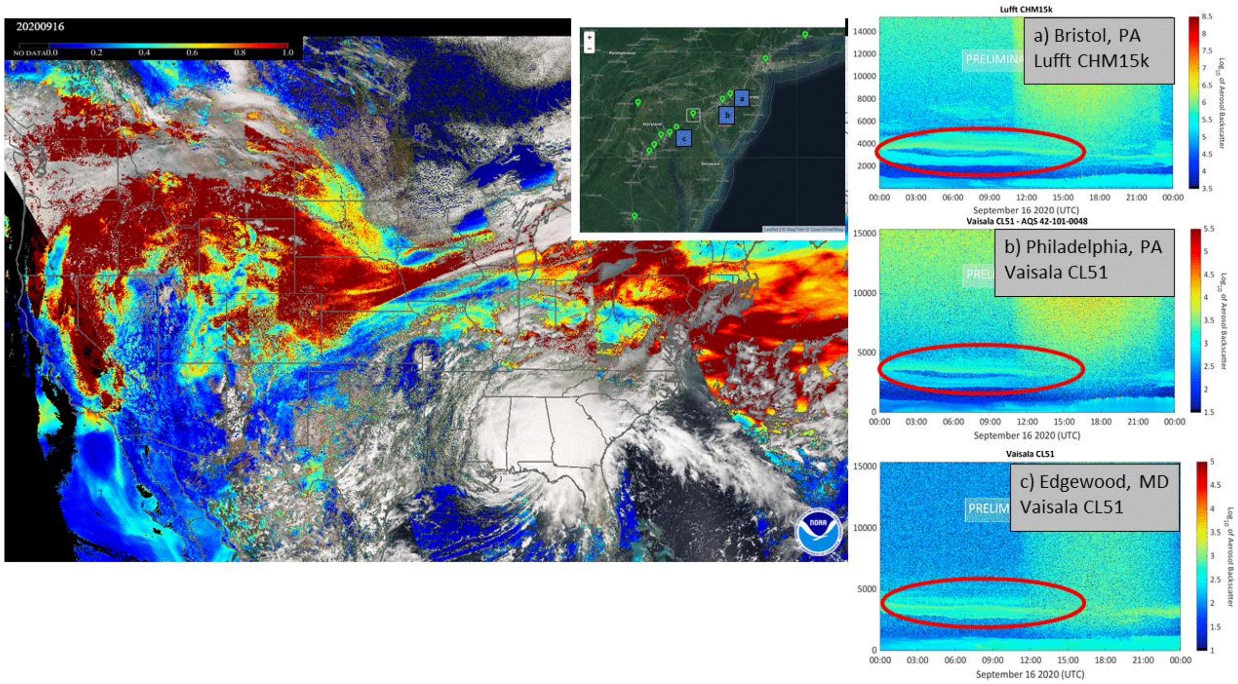
#### 4.3.5.2 Ground-Based Measurements

Ground-based remote sensing networks across the U.S. serve a wide range of functions, such as the highly operational surface weather observation stations which contain several remote-sensing instruments in combination with in situ instruments used to provide continuous observations to generate routine weather reports to more research based networks, such as the NASA Micro-Pulse LiDAR Network (MPLNET), a small federated network of compact LiDARs designed to measure aerosol and cloud vertical structure, and boundary layer heights. The combination of these networks provides relevant data on surface visibility, the vertical distribution of aerosols, boundary layer heights, AOD, and total column NAAQS gaseous pollutants.

The combined Automated Surface Observing System (ASOS)/Automated Weather Observing System (AWOS) networks consist of over 1,000 sites across the U.S., with ASOS containing over 900 sites. The primary remote sensing measurement at ASOS/AWOS sites is surface visibility. The visibility measurement uses a forward scatter sensor and detector to measure the attenuation of light by scattering and absorption at the wavelength of 550 nm. The sensor measures a 1-minute avg extinction coefficient and reports a 10-minute avg. The 550 nm measurement is very sensitive to $PM_{2.5}$ and therefore can be used to understand reduced visibility caused by wildland fire smoke. The ASOS/AWOS sites also used ceilometers for reporting cloud-based heights. Ceilometers are a type of LiDAR, capable of providing vertical profile information on aerosols in the troposphere through the attenuation of backscatter from aerosols. While NOAA operates a large network of ceilometers as part of ASOS, the instruments are not currently configured to report the aerosol backscatter profiles, which can be used to define aerosol layer heights and derive a mixing layer height/planetary boundary layer height. Ceilometer technology is being implemented by U.S. EPA Photochemical Assessment Monitoring Station (PAMS) program.

Recent updates to the U.S. EPA PAMS network require the stations to measure and report an hourly mixing layer height. This measurement requirement will be fully implemented by June 2021 and is primarily being satisfied through the installation of ceilometers across the network sites. While state and local agencies are required to only report an hourly mixing layer height, an U.S. EPA collaboration with the UMBC, NASA, and NOAA is focused on the development of a near-real-time data system to archive and display ceilometer backscatter profiles, aerosol layer heights, and planetary boundary layer heights (PBLH) from PAMS and non-PAMS ceilometers into the UCN [https://alg.umbc.edu/ucn/; UMBC (2021)]. The UCN will use a common algorithm to determine PBLH (Caicedo et al., 2020) and display near-real-time aerosol backscatter vertical profiles which can be used to track the vertical structure of aerosol plumes, including wildland fire smoke, as the plumes are transported across the U.S. as shown in Figure 4-4.

The NASA MPLNET is a global federated LiDAR network which supports research and the NASA Earth Observing System (EOS) program (Wielicki et al., 1995). Value-added network data sets are made available to the community via an online repository [http://mplnet.gsfc.nasa.gov; NASA (2021); Campbell et al. (2008)]. The micropulse LiDAR operated at 532 nm in contrast to ceilometers which operate in the 900 nm range or 1,064 nm, which provides the micropulse LiDAR system the benefit of being more sensitive to $PM_{2.5}$.




Note: Aerosol backscatter profiles from ceilometers located at air quality monitoring sites (a) Bristol, PA; (b) Philadelphia, PA; (c) Edgewood, MD show the smoke layer being transported above the boundary layer, with little to no impacts to surface air quality.

Source: Unified Ceilometer Network—https://alg.umbc.edu/ucn/. UMBC (2021).

**Figure 4-4 Image of western U.S. wildfire smoke transported to the Northeast U.S. as captured in the Visual Infrared Imaging Radiometer Suite (VIIRS) True Color Image over plotted with VIIRS aerosol optical depth for September 16, 2020.**

For over two decades the NASA AErosol RObotic NETwork (AERONET), a federated association of ground-based sun and sky scanning radiometer, has provided high-temporal-resolution measurements of the optical, microphysical, and radiative properties of aerosols. One of the primary data products, columnar AOD, is used as a primary validation resource for satellite validation of AOD. The Angstrom exponent from the measurements can be used to provide an estimate of the dominant aerosol size within the AOD measurement (Giles et al., 2019). Similar to AERONET, the Pandonia Global Network (PGN) is an emerging federated global network of ground-based spectrometers lead by NASA and the ESA and was developed for validation of trace gas column abundances from satellites such as TROPOMI (Judd et al., 2020; Zhao et al., 2020). The instrument, called pandora, is a UV/VIS spectrometer and currently provides near-real-time data products of total column $O_3$ and $NO_2$, tropospheric $NO_2$, and a derived $NO_2$ surface concentration, with tropospheric column $CH_2O$ moving from a research data product to a standard data product in the coming year (Szykman et al., 2019). The number of AERONET and PGN sites across the U.S. can vary on a year-to-year basis as both instruments are often used to support research field campaigns, at the end of 2020 AERONET reported approximately 100 active sites and PGN 14 active sites.

## 4.4 Ambient Air Quality Monitoring Data Availability and Quality

### 4.4.1 Overview

Observational air quality data is used in many facets of wildland fire smoke management from first-responder force protection and public health messaging where real-time data availability is critical, to regulatory NAAQS review and public health research (e.g., epidemiologic studies) where delayed data access is acceptable but rigorous data quality assurance/quality control (QA/QC) review is required. This section discusses observational air quality data availability and relative data quality that is routinely used by wildland fire smoke managers, public health officials, and researchers.

### 4.4.2 U.S. EPA Routine Regulatory Data Availability

As described above, near real-time measurements of $PM_{2.5}$ and $O_3$ are reported from state, local and tribal air monitoring agencies to AirNow (Table A.4-3). The data are then made publicly available through NowCast reporting of the AQI. The raw hourly data for $PM_{2.5}$ and $O_3$ as well as all other reported real-time air pollution and meteorological parameters are stored and available to the AirNow technical community through the website www.AirNowTech.org. AirNow-Tech is a password-protected website for air quality data management analysis, and decision support. AirNow-Tech is primarily used by the federal, state, tribal, and local air quality organizations that provide data and forecasts to the AirNow system, as well as researchers and other air data users. Automated availability of large amounts of AirNow data can be accomplished by registered users through accessing the AirNow application programming interface (API). There are important distinctions between the AirNow data system and the AQS database described below. First, to ensure real-time availability of data in AirNow, data are reported as soon as practical after the end of each hour. Therefore, data are available to support forecasting and reporting of the AQI but are not used for regulatory decisions until all QA/QC checks are performed and validation of data is certified by the responsible state/local/tribal agency. Second, data reported to AirNow include many monitoring stations for communities outside the U.S. For example, air monitoring programs for Canadian Provinces and cities report their $PM_{2.5}$ and $O_3$ data to AirNow. However, data from outside the U.S. are usually not reported to the AQS data system described below.

U.S. EPA's long-term repository of data is provided by the AQS. The AQS contains ambient air pollution data collected by state, local, and tribal air pollution monitoring agencies. The data set includes data from both automated methods reported to AirNow, but also from manual methods where data are not available for several weeks to months due to post-sampling laboratory analysis. In addition to pollutant concentrations and meteorological data, AQS contains descriptive information about each monitoring station (including its geographic location and its operator), and data quality assurance/quality control information. While data are reported to AirNow within minutes after the end of an hour, data are not required to be reported to AQS until 90 days past the end of a calendar quarter. This lag and difference in data reporting allow monitoring agencies the time needed to validate ambient air monitoring data for NAAQS compliance. Data reported to both AQS and AirNow are matched on a routine basis with AQS data overwriting any reported data to AirNow. This allows monitoring agencies the opportunity to invalidate data in one location while ensuring validation decisions are carried through to both databases. By May 1st of each year, monitoring agencies are required to "certify" (U.S. EPA, 2019c) their criteria pollutant data used for NAAQS compliance determinations so that it is available to use in design value calculations. A user friendly portal to access reports and data from AQS data is available at: https://www.epa.gov/outdoor-air-quality-data .

### 4.4.3 Temporary/Incident Response Data Availability

The temporary $PM_{2.5}$ monitors deployed by federal, state, tribal, and local agencies for incident response typically report hourly data through satellite communications. The AirNow Fire and Smoke Map project, a collaborative effort between IWFAQRP and U.S. EPA collects these data through the AirSis and Western Regional Climate Center (WRCC) data feeds (AirNow, 2021b, c). Following quality assurance checks including flow rate, internal humidity, battery levels, and measurement values within a feasible range, the data are made available through the AirNow Fire and Smoke Map. PM data from permanent monitors (Section 4.3.2) obtained through the U.S. EPA AirNow system (Section 4.4.2), as well as sensors (Section 4.4.4), are also included in AirNow Fire and Smoke Map. The system also provides the locations of large fire incidents from the U.S. National Interagency Fire Center's active incident feed and satellite based active fire detections and smoke plume locations (Section 4.3.5.1.1) from the NOAA Hazard Mapping System. Currently, the system functions as an operational data viewer—data is not available for download and viewing is limited to data <10 days old. Data downloads (<10 days old) for temporary and permanent monitors are available through the USFS AirFire V4.1 smoke monitoring system [https://tools.airfire.org/monitoring; USFS (2021a)], a predecessor to the AirNow Fire Map. Limited historical PM data from some temporary monitors can be accessed through the WRCC [https://wrcc.dri.edu/cgi-bin/smoke.pl; WRCC (2021)]. No comprehensive archive of temporary $PM_{2.5}$ monitor data is currently available to researchers, land managers, or the public.

The www.airfire.org website provides visualization tools for ARAs to evaluate temporal and spatial smoke trends, and how PM concentrations vary between observational surface measurements and smoke prediction model estimates. The temporospatial trends and smoke model performance are important for ARAs to contextualize with current fire conditions and observed smoke production during large wildfire events. Diurnal smoke behavior is particularly important for predicting how the smoke will impact some areas, especially when the smoke dispersion is dominated by terrain driven winds in foothill and mountain communities. A limitation to the publicly available AirNow data is that it reflects the NowCast concentration, not necessarily the current concentration at any given time, so it could be anywhere from 1 to 3 hours behind providing the appropriate trend. This is important for public health officials when tracking concentrations, especially when they are trying to provide schools and athletics information on whether outdoor activities are safe or if air quality is remaining in the unhealthy range.

AirNow does provide another link to the information—this is the primary public-facing sites and resources provided to better understand the trends in air quality. The forecasting reported on AirNow by local air pollution control districts are quite often accurate for a 24-hour period; however, there is a limitation in how the reporting area is determined. Quite often the reporting area is based on the largest metropolitan area with an air quality forecast. This forecast may be an accurate estimate of smoke impact if the area has uniform terrain. However, reporting areas for cities in the foothills or neighborhoods with substantial elevation change the actual smoke concentration may be substantially different than predicted due to terrain induced drainage flows. So even when air quality improves in the closest metropolitan area, the smoke may linger and take longer to dissipate in certain areas which may change the 24-hour estimate of the AQI. In foothill communities, when there are terrain-driven winds, these communities will often see delayed AQI improvement compared to centrally located monitors because of how the smoke will transport with upslope and downslope winds following typical diurnal patterns. The delay in AQI improvement has been particularly evident during extended periods of high pressure over fires where smoke continues to hang in the valleys over a period of days and sometimes weeks. Therefore, the smoke reporting for certain areas, especially in the wildland–urban interface (WUI) and in foothill communities provide AQI prediction challenges where actual air quality is not adequality represented by the closest central monitoring site.

### 4.4.4 Sensor Data Availability

The current business use case for most commercially available air quality sensors involve either local data storage for end user use only or vendor specific cloud-based data telemetry, storage, quality assurance review, and graphical presentation of summary monitoring data. Most air quality sensor manufactures that maintain cloud-based systems do so to provide secure storage and analysis tools for each end user. 2B Tech (2021), Clarity (2021), and PurpleAir (2021) are examples of manufacturers that do allow the end users to choose whether to keep their monitoring data private or allow for public dissemination of their data through each manufacturers proprietary map-based web portals as part of the sensor registration process. The Environmental Defense Fund (EDF), OpenAQ, and other nongovernmental organizations have undertaken independent initiatives that advocate for the development of a centralized repositories of data collected from ambient air quality sensors that includes the development of data standards and definitions of terms with the vision of making integrated air quality sensor from all manufacturers publicly available (EDF Air Sensor Workgroup, 2021; OpenAQ, 2021). The value of publicly available sensor data was demonstrated by U.S. EPA and USFS as part of their pilot AirNow Fire and Smoke Map project in 2020 (AirNow, 2021a). The pilot used the data from a single manufacturer (PurpleAir) due to the relatively large number of deployed sensors, documented $PM_{2.5}$ sensor performance (Barkjohn et al., 2020), and the public availability of their data. However, there is currently no centralized publicly accessible air quality data repository from ambient sensors that are available for wildland fire incident teams, air quality regulators, researchers, or public health officials to access during wildland fire events.

### 4.4.5 Remote Sensing Data Availability

Data latency and reliable data availability are critical attributes for the use of satellite data, particularly for air quality uses associated with smoke plume tracking and improved predictions of pollutants distributions during active wildland fires. Operational satellite instruments such as VIIRS, GOES-ABI and TROPOMI are designed for low data latency and reliable data availability because of the reliance on such instruments to inform weather and air quality forecast. Such considerations are usually not a high priority for research satellites, however the direct broadcast *X*-band downlink and near-real-time science data production software International MODIS/AIRS processing package (Strabala et al., 2003) implemented for the MODIS sensors aboard the Terra and Aqua satellites facilitated use of the data for tracking wildland fire plumes to improve $PM_{2.5}$ forecast (Al-Saadi et al., 2005). The availability and latency for satellite and ground based remote sensing data is summarized in Table A.4-4 and Table A.4-5, respectively.

### 4.4.6 Measurement Data Quality

FRM and FEM methods include instrument design requirements, strict performance specifications, and routine calibration and maintenance requirements. In addition, monitoring requirements (U.S. EPA, 2019b) prescribe routine onsite auditing of instrument performance, rigorous data quality assurance/quality control review of all regulatory measurements, and adherence to siting criteria (e.g., distance from obstructions). Monitoring agencies carry out and perform ambient air monitoring in accordance with the U.S. EPA's requirements and guidance as well as often meeting their own state monitoring needs that may go beyond the minimum federal requirements. As previously stated, air quality data obtained from state, local, and tribal monitoring sites are reported to U.S. EPA's AQS database, along with other information, and are used for determining compliance with the NAAQS, assessing effectiveness of mitigation strategies, characterizing local, state, and national air quality status and trends, and associating public health outcomes with air pollution concentrations/population exposures. Therefore, regulatory measurements are the highest quality air pollution measurements available.

Nonregulatory instruments used for temporary incident response measurements like the ARA deployed E-BAM and E-SAMPLERS are maintained/calibrated to manufacturer specifications by IWFAQRP at their Lakewood, CO facility prior to field deployment each fire season. The USFS conducted tests on these two devices ranging from 30 to 1,700 μg/m$^3$ under smoke conditions against a gravimetric, filter-based U.S. EPA FRM sampler (Trent, 2006, 2003). On average, both the E-SAMPLER and the E-BAM samplers overestimated the mass concentration by approximately 13% over the FRM, yet correlation coefficients were very high, over 0.96 and over 0.99, respectively (Trent, 2003). The IWFAQRP instruments are received, installed, and maintained by trained ARA professionals following established program SOPs. The data quality from other state, local, or tribal agency temporary incident response instruments are expected to be of similar quality to IWFAQRP deployments when following their established training and instrument SOPs.

Raw $PM_{2.5}$ concentration data from air quality sensors is generally considered qualitative during wildland fire smoke events due to the general lack of smoke specific performance testing, routine maintenance and calibration procedures, and data QA/QC screening and validation. There is also a recognition that certain sensor systems are better categorized by objective testing organizations such as U.S. EPA (U.S. EPA, 2020c), the South Coast Air Quality Management District's Air Quality Sensor Performance Evaluation Center (SCAQMD, 2021), and the European Commission Joint Research Center (JRC, 2021), and that sensor networks deployed, characterized relative to FRM/FEM measurements, and maintained by governmental/professional organizations may be of higher quality. Adoption of formal air quality sensor performance targets, calibration, maintenance, data quality review guidelines, and certification requirements that are currently being investigated by U.S. EPA (Duvall et al., 2021a, b) would provide a path forward for ensuring that future air quality sensor data would better serve the observational air quality monitoring requirements of the wildland fire smoke management community.

## 4.5 Challenges in Ambient Smoke Monitoring

Wildland fire smoke events can produce extreme near-field air pollutant concentrations that exceed monitoring instrument linear dynamic range and reporting limits, cause analytical interference(s), and generally increase the uncertainty in reported air pollution concentrations. In many areas of the country wildfire smoke is responsible for the highest air pollution concentration values experienced and may dominate the local populations exposure to air pollution (e.g., $PM_{2.5}$) on an annual basis. Some initial evaluations of UV-photometric FEM $O_3$ instruments (Landis et al., 2017; Long et al., In Press) and visible spectrum FEM $PM_{2.5}$ instruments (Landis et al., 2021) have documented measurement accuracy degradation under smoke conditions. In addition, wildland fire smoke events present many inherent measurement, quality assurance, data latency, data integration, data availability, and communication challenges for land management, wildland fire smoke management, air quality management, and public health officials including:

- Wildland fire events and downwind smoke impact zones occur disproportionally in areas of the U.S. having diffuse population centers and lacking U.S. EPA regulatory air quality monitoring infrastructure typically used to measure AQI and communicate appropriate public health messages. Complex terrain and unpredictable smoke plume behavior can also complicate accurate determination and spatial interpolation of AQI and the associated public health recommendations for limiting smoke exposure.
- Wildland fire smoke can be highly spatially and temporally variable. Smoke can be confined to topographic areas such as valleys or in specific vertical or meteorological layers (e.g., inversions), meaning that air quality monitors only a few kilometers apart can report dramatically different concentrations. Smoke concentrations can change substantially over short time periods as fire activity and meteorological dispersion changes make it difficult to predict and manage hazardous conditions (e.g., measured average hourly concentration values may not match the experience of smoke even at that location due to subhourly temporal fluctuations).
- Wildland fire smoke can transport for long distances. Smoke plumes from specific wildfires have been traced across continental or even oceanic/transcontinental scales. Air pollution concentrations can be significantly elevated thousands of km away without an obvious connection to distant fire events.
- The availability, validity, comparability, and integration of observational air quality measurements during wildland fire events is improving (e.g., sensor data pilot, smoke modeling tools); however, there is a long way to go to enable real-time (low latency), integrated, and publicly available data and modeling tools that are required for effective management activities at local, state, and regional scales.

The air quality monitoring challenges during wildland fire events are inherently linked to the associated limitations in current U.S. EPA regulatory monitoring networks. The objectives of these networks do not include smoke monitoring. The current network designs that prioritize densely populated urban and suburban areas where most anthropogenic air pollution sources are concentrated result in a lack of network site density and spatial/elevation distribution of monitors in more remote areas where wildland fire events are more likely to occur. Issues with data telemetry, latency, and QA/QC review culminate to create a situation where wildland fire smoke impacts are not well captured by existing regulatory networks. Temporarily emplaced monitors, remote sensing, and air quality sensors offer future opportunities to supplement regulatory monitoring infrastructure. However, as discussed above, these observational monitoring technologies have their own issues with accuracy, reliability, and availability of measured concentration values and the ability to quickly emplace and telemeter data to fill the most important gaps in spatial coverage.

## 4.6 Recommendations

Currently, the fundamental understanding of wildland fire source emissions, the impact of smoke on ambient air quality, the estimation of human exposures, the quantification of adverse health outcomes, and the ability to develop and validate predictive deterministic air quality models are predicated on accurate measurements of criteria air pollutants and their precursors in smoke. This chapter presented and discussed the contemporary sources of ambient air quality monitoring data, the relative accuracy of data sources, the latency and availability of data, and the tools for accessing and analyzing air pollution monitoring data and smoke dispersion modeling in the U.S. While U.S. EPA's current regulatory monitoring network objectives do not include smoke monitoring, it is evident that recent advances in measurement technologies, cloud computing capabilities, and online data accessibility tools have improved the national capacity to measure, predict, and disseminate public health information on smoke impacts from wildland fire events. However, it is also clear that there are fundamental gaps in the ability to (1) accurately measure air quality impacts from wildland fire smoke over relevant spatial and temporal scales, (2) integrate and archive available observational data streams into common data format standards, and (3) provide timely access to integrated data analysis and visualization tools necessary for smoke management and public health officials to take effective control and abatement actions.

Based on these gaps, enumerated below are several actions that could help address the identified challenges and advance national capabilities for wildland fire smoke monitoring:

- Establishment of a program to evaluate the performance of U.S. EPA designated FRM/FEM regulatory monitors under wildland fire smoke conditions.
- Inclusion of wildland fire smoke monitoring as an air quality monitoring objective for areas of the country with recurring wildland fire smoke impacts.
- Establishment of guidelines for the evaluation of commonly used commercially available nonregulatory instruments and air quality sensors under wildland fire smoke conditions.
- Establishment of data and QA/QC review standards for commonly used commercially available nonregulatory instruments and air quality sensors.
- Development of mobile air quality monitoring capabilities around wildland fire events as an added capability for ARAs working on large incidents particularly in more remote areas with limited existing monitoring infrastructure. Mobile wildland fire smoke measurements would provide public health officials the means to inform the placement of their temporary stationary monitors, evaluate the wildland fire smoke exposure risks across multiple communities, and to provide timely and actionable public safety information.
- Collaborative effort across federal agencies (e.g., U.S. EPA, USFS, NOAA, NASA) to establish common data sharing agreements for remote sensing data.
- Development of a publicly available cloud-based data integration and visualization platform for all available regulatory, nonregulatory, air quality sensor, and remote-sensing data streams for wildland fire smoke management and wildland fire smoke impact analysis. AirNow serves some of this capacity now and could be enhanced with the suggested functionalities.

Through these actions it is possible to chart a collaborative interagency path forward in addressing current wildland smoke monitoring challenges such as unknown accuracy of air pollution monitors in wildland fire smoke, lack of network site density and spatial/elevation distribution of monitors, data telemetry and latency issues, and the availability and comparability of wildland fire smoke impacted monitoring data products. In addition, the collaborative nature of the proposed actions would allow for the formation of a constructive community of wildland fire smoke practitioners and researchers focused on improving the quality, integration, and availability of air quality monitoring data.

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# CHAPTER 5 AIR QUALITY MODELING OF WILDLAND FIRE

## 5.1 Background

Wildland fires (i.e., prescribed fire and wildfire) directly emit fine particulate matter ($PM_{2.5;}$ particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm ) and gaseous pollutants emitted from fires can also form secondary $PM_{2.5}$ and ozone ($O_3$) in the atmosphere (Prichard et al., 2019; Urbanski, 2014; Hu et al., 2008). Estimating emissions and concentrations of pollutants formed from wildfires is challenging due to variability in fuel consumed, fuel types, fuel moisture, plume dynamics, and complex nonlinear chemistry (Prichard et al., 2019; Jiang et al., 2012). A realistic characterization of $O_3$ and other secondary pollutant formation in a wildfire plume is also dependent on capturing the plume's surrounding chemical and physical environment, factors that evolve as the plume moves further downwind from the fire.

Prescribed fire is a relatively efficient, cost-effective tool implemented by land managers for a range of uses, including ecosystem maintenance (Kobziar et al., 2015) and wildfire mitigation (Prichard et al., 2010). While the use of prescribed fire as a land management tool is common in some parts of the contiguous U.S., both the specific land management goals and the response of the landscape to prescribed fire can vary significantly (Ryan et al., 2013). For these reasons, it has been historically difficult to synthesize both the environmental trade-offs between wildfire and prescribed fire, as well as the behavioral influence of prescribed fire on wildfire activity (e.g., changes in intensity, risk of ignition, fire size, etc.).

This chapter presents a novel analysis evaluating air quality trade-offs across multiple fire management strategies for two wildfires: Timber Crater 6 (TC6) Fire in 2018 and Rough Fire in 2015. CHAPTER 3 contains general details and maps describing these fires. In both cases, detailed alternative burn scenarios were developed with fuel information from multiple sources. Actual and alternative burn scenarios were then simulated with air quality modeling to estimate surface concentrations of $PM_{2.5}$ and $O_3$. Comparing the air quality impacts across different burn scenarios for each fire case study offers insights into relative air quality impacts from hypothetical land management approaches, although downwind transport and resulting air quality impacts near population centers can be strongly influenced by locally specific features like terrain and meteorology.

### 5.1.1 Emissions of Wildland Fires

The relative amounts and chemical composition of emissions depend upon the fuel characteristics, combustion conditions, and meteorological conditions (Urbanski, 2014). Additionally, these factors are interrelated; for example, the combustion intensity is dependent on the meteorological conditions (temperature, relative humidity and wind conditions) and the fuel characteristics [structure, moisture, and loading; Surawski et al. (2015)]. Meteorology can also modulate combustion conditions, with strong winds increasing the rate and extent of spread and peak heat release rate (i.e., intensity).

The modified combustion efficiency, defined as MCE = excess $CO_2$/[excess CO + excess $CO_2$], is widely used as an indicator of combustion conditions. MCEs greater than 0.9 are generally considered flaming dominated and lower MCEs are smoldering dominated. Grasses and other fine fuels (<1/4″ diameter and large surface to volume ratios) tend to burn in the flaming phase. Coarse wood, duff, and organic soils tend to burn in the smoldering phase. Fuel loading, density, and geometry also impact the combustion phase (e.g., densely packed fine fuels will smolder). Many wildland fires burn in landscapes with a variety of fuel types, structures, and moisture content and will therefore exhibit both flaming and smoldering conditions simultaneously.

The fuel moisture content is a critical factor that impacts combustion conditions. Energy is lost in evaporating the water in the fuel rather than volatilizing fuel components needed to sustain flaming combustion. Fuels with higher moisture content take longer to ignite, may smolder before transitioning to flaming, have shorter flaming and longer smoldering durations, lower peak heat release rate, as well as lower and more variable fuel consumption (Possell and Bell, 2013; Chen et al., 2010). Additionally, the moisture content impacts the composition of the emissions. carbon monoxide (CO), volatile organic compound (VOC), ammonia ($NH_3$), and particulate matter (PM) emission factors increase while carbon dioxide ($CO_2$), nitrogen oxides ($NO_X$), and elemental carbon (EC) generally decrease with increasing moisture (May et al., 2019; Tihay-Felicelli et al., 2017; Chen et al., 2010). PM emissions are especially sensitive to fuel moisture. PM emission factors can be larger than CO emission factors for some fine fuels (e.g., litter, pine needles, etc.) at high fuel moistures [e.g., above 60% dry basis; Chen et al. (2010)].

Most emission factor compilations group emission factors by ecoregions to aggregate the impacts of fuel chemistry, structure, and to some extent moisture (Prichard et al., 2020; Andreae, 2019; Akagi et al., 2011). The emissions model will then predict how much fuel is consumed (or emitted) during the flaming or smoldering phases. The Smoke Emissions Reference Application (SERA) described in Prichard et al. (2020) is the most extensive compilation of smoke emission factors for North American fires to date. However, knowledge gaps persist for emissions factors for wildland fires as summarized by [Prichard et al. (2020); derived from Figure 1, Table 3], resulting in limited information with respect to:

- Wildfire emission factors: Emission factors are predominantly from laboratory studies (72% of the observations); field data are 85% from prescribed fires and 15% from wildfires.
- Smoldering emission factors: Smoldering emission factors account for 31% of the prescribed fire observations and 50% of wildfire observations, but wildfires have no emission factors for long-term (residual) smoldering conditions.
- Fuels that tend to smolder: Most emission factor observations are from western conifer forests, eastern conifer forests, and shrublands, but there are few observations for duff, coarse woody debris, and peat from these regions.

- PM and VOC speciation: PM composition data is largely limited to black carbon and limited VOC data exists, particularly for field data; most emission factor observations are the major pollutants of CO, $CO_2$, methane ($CH_4$), and $PM_{2.5}$, but a range of compounds have over 100 observations (propene, acetylene, methanol, formaldehyde, $NH_3$, NO, $NO_2$, $NO_X$, hydrogen cyanide [HCN], sulfur dioxide [$SO_2$]).

In comparing emissions from wildfires and prescribed fires the different meteorological conditions, potentially different fuels, and combustion conditions mean that emission factors will be different for each type of fire, even in the same region. For example, Urbanski (2014) compared MCEs for wildfires and prescribed fires in northwest conifer forests and found an average MCE of 0.883 ± 0.010 for wildfires and 0.935 ± 0.017 for prescribed fires. However, the type of fuel that is consumed may be an important factor because prescribed fires and wildfires in the northern Rocky Mountains both had lower MCEs (~0.87) that were attributed to a larger fraction of coarse woody debris (Urbanski, 2013). While meteorological, fuel, and combustion parameters are factored into emissions estimation, there is still a need to understand whether emissions modeling systems accurately capture the differences between fire types.

### 5.1.2 Using Air Quality Models to Estimate Wildland Fire $PM_{2.5}$ and Ozone Impacts

Quantifying the contribution of wildland fire to ambient $O_3$ and $PM_{2.5}$ is important for air quality alerts, air quality mitigation programs, and multiple regulatory programs including National Ambient Air Quality Standards (NAAQS) and Regional Haze. It is important to understand how wildland fires impact air quality and regional haze so that anticipated changes in land management (i.e., more prescribed fires) could potentially minimize air quality degradation while still meeting ecological goals as well as potentially reducing the impact of wildfire.

Photochemical grid models can provide information about how air quality would change based on changes in emissions due to different types of land management choices (Hu et al., 2008). The Community Multiscale Air Quality [CMAQ; www.epa.gov/cmaq; U.S. EPA (2020a)] model includes emissions, chemical reactions, and physical processes such as deposition and transport. The CMAQ model has been used to estimate the air quality impact of wildland fires as a collective source group (Kelly et al., 2019) and for specific fires (Baker et al., 2018; Zhou et al., 2018; Baker et al., 2016).

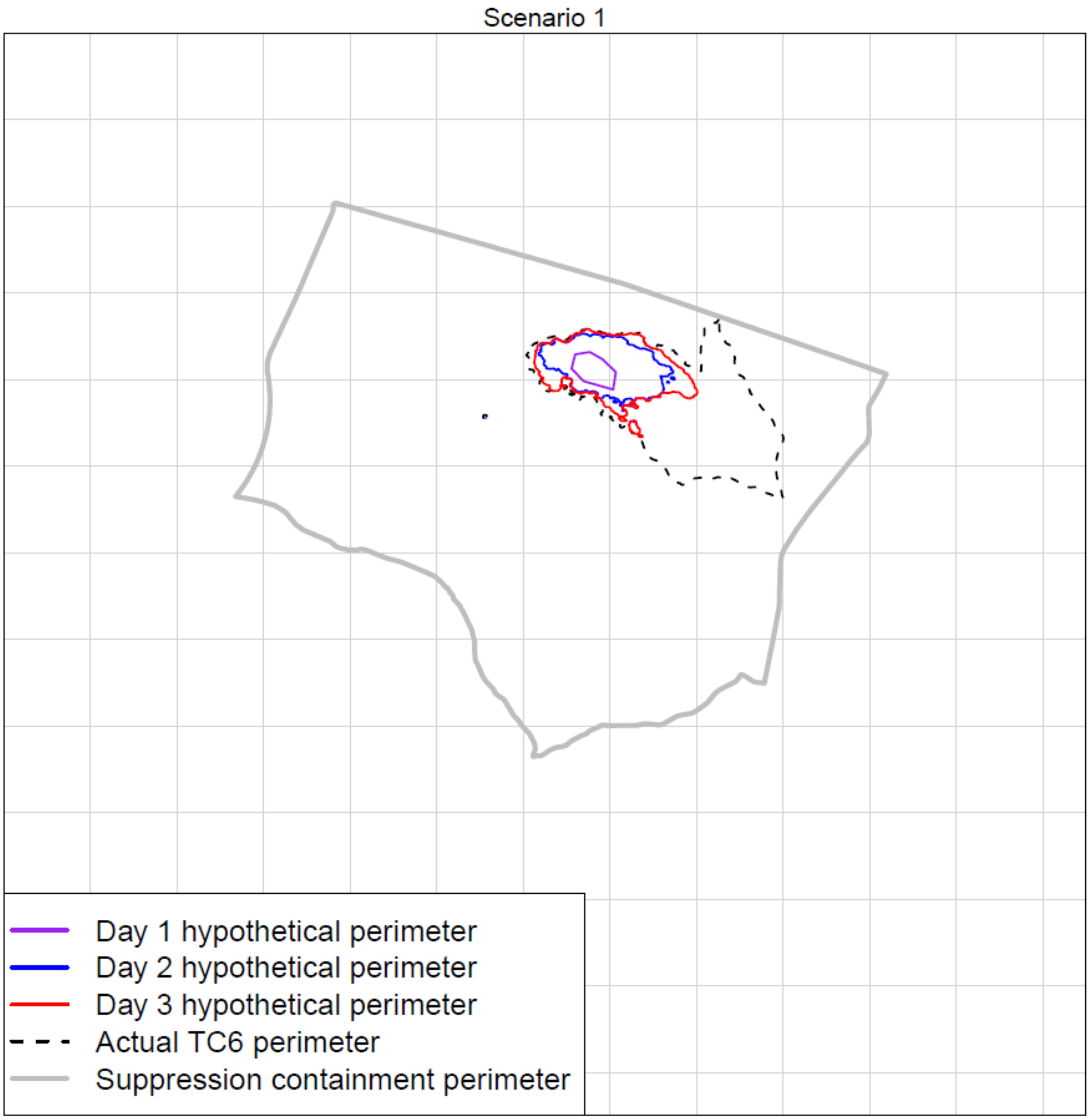
Photochemical grid models provide continuous spatial and temporal estimates of smoke impacts from wildfires, which is particularly useful in areas not covered by ambient measurements (O'Dell et al., 2019). However, fire behavior and associated smoke characteristics can vary substantially by region (Brey et al., 2018). Accurately representing wildfire smoke in models for different geographic areas is an ongoing effort that will continue to be important as landscapes evolve due to climate change and human development (Ford et al., 2018; Liu et al., 2016; Yue et al., 2013). Detailed case studies, like the two in this report, provide some constraints on the representation of wildfire smoke in models for specific areas, but more work is required to improve these estimates at both regional and global scales (Liu et al., 2020; Garcia-Menendez et al., 2014, 2013).

Previous applications of CMAQ for specific fire plumes show a reasonable representation of local to continental scale transport (Kelly et al., 2019; Baker et al., 2016). The modeling system treatment of plume rise and transport is best when supplied with accurate activity data including fire size and timing (Baker et al., 2018; Zhou et al., 2018). Performance related to $PM_{2.5}$ impacts from wildland fire are mixed and do not seem systematically biased high or low (Baker et al., 2018; Koplitz et al., 2018; Wilkins et al., 2018; Baker et al., 2016). This modeling system tends to overestimate $O_3$ impacts from wildland fire at the surface (Baker et al., 2018; Baker et al., 2016). Predicting wildland fire impacts on $O_3$ is challenging because formation can be highly variable in time and space. Fresh nitric oxide emissions at the fire tend to inhibit $O_3$ formation as chemical destruction reactions outpace production. As the plume moves further downwind $O_3$ may be formed at the edges of the plume where sunlight and precursors are abundant. Atmospheric transport processes are also important as $O_3$ may be formed in smoke plumes but not necessarily mix to the surface.

### 5.1.3 Case Study: Timber Crater 6 (TC6) Fire

The TC6 Fire burned approximately 3,000 acres in Crater Lake National Park from July 21 to July 26, 2018. The fire covered lands managed by multiple Federal agencies. This fire was chosen as a case study for this report because land managers in the area determined that reduced fuel loading from previously managed land slowed fire progression enough to allow for successful suppression (e.g., burning out fire lines). As a result, the TC6 Fire had a smaller total area burned than might have occurred without those suppression efforts.

Three hypothetical scenarios, as detailed in 0, were developed to examine the air quality impacts of different fire management strategies compared to the actual TC6 Fire. Scenario 1 assumed a smaller and shorter duration fire than the actual fire, attributed to less fuel from more intensive land management (Figure 5-1). Scenarios 2a and 2b assume more fuel in the area due to a lack of past land management. Both Scenarios 2a and 2b are larger than the actual fire and are longer in duration than the actual fire. Hypothetical Scenario 2b is the largest fire extending outward to a contingency perimeter where fire suppression would be aided by roadways and other existing fire breaks. All of these scenarios used fuel data based on a consistent approach which is described in the following sections.

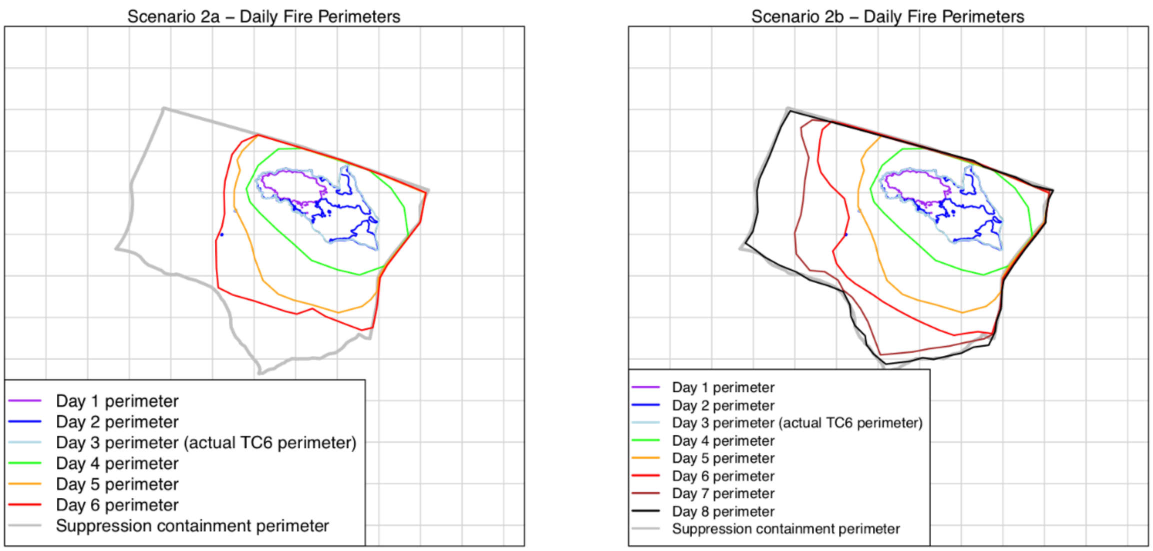



TC6 = Timber Crater 6.

Note: The fire perimeter of the actual Timber Crater 6 Fire is also shown as the dashed line. The solid gray outline shows the fire suppression contingency perimeter which is considered the maximum extent of wildfires in this area. The total area assumed burned with Scenario 1 is delineated by the Day 3 perimeter.

**Figure 5-1 Daily fire perimeters for the smaller Timber Crater 6 (TC6) hypothetical fire (Scenario 1).**

Each of the hypothetical scenarios were based on expert judgement of land managers familiar with Crater Lake National Park, the fuels in the area, meteorology during the TC6 Fire, existing fire breaks (e.g., roadways), and additional suppression techniques that would have been employed if the fire had spread faster than the actual fire. Actual fire perimeters from the TC6 Fire were used for the first 3 days of the larger hypothetical scenarios with Day 3 being the actual final perimeter of Timber Crater 6. These hypothetical scenarios were not based on fire behavior or fire spread models. Two hypothetical scenarios (2a and 2b) were developed to represent larger fires than the actual fire (Figure 5-2). Both larger hypothetical scenarios (2a and 2b) cover a larger area and extend more days than the actual fire.




TC6 = Timber Crater 6.

Note: The solid gray outline shows the fire suppression contingency perimeter which is considered the maximum extent of wildfires in this area.

**Figure 5-2 Daily fire perimeters for the larger Timber Crater 6 (TC6) hypothetical fires (Scenarios 2a and 2b).**

### 5.1.4 Prescribed Fire near Crater Lake National Park

Land management practices in and near Crater Lake National Park include prescribed fire and mechanical thinning. Some of the leftover fuel from mechanical thinning is sold as timber and some is burned in slash piles during the winter. Multiple prescribed burns have been conducted in the area (Figure 5-3), some of which intersect the TC6 Fire perimeter: Cornerstone in 2007 (no specific dates known), Timber Crater 1 and 2 in 2001 (no specific dates known), and Timber Crater 1978 in 1978 (no specific dates known). More recent prescribed fires (not named) were conducted in this area in September 2019 (13−15 and 26−28). Because the days of the September 2019 prescribed fires were presumed to match criteria for prescribed fire in the region, this time period was used for modeling both actual prescribed fires during that period and provided a basis for modeling other prescribed burn units from previous years. Each prescribed fire (e.g., actual 2019 prescribed fires, Cornerstone, Timber Crater 1 and 2, and Timber Crater 1978) were modeled for these 2019 dates but in separate model simulations so they would not interact with each other.


Rx = prescribed burn.

**Figure 5-3 Fire perimeter of the actual Timber Crater 6 (TC6) Fire, multiple wildfires that yielded positive resource benefits, and multiple prescribed fires.**

### 5.1.5 Case Study: Rough Fire

The Rough Fire burned in parts of the Sierra National Forest, Sequoia National Forest, and Kings Canyon National Park between July 31 and October 1, 2015 [https://www.nps.gov/seki/learn/nature/rough-fire-interactive-map.htm); NPS (2016)]. This wildfire covered approximately 150,000 acres of land managed by multiple Federal agencies. The Rough Fire was chosen as a complement to the TC6 Fire due to its much larger size and duration.

Land managers were able to suppress the Rough Fire at several points where land had been previously managed. One such area was the Sheep Complex Fire in 2010 (~9,000 acres), which resulted in less available fuel and provided a break to stop fire progression. The Sheep Complex Fire in 2010 was a multimonth wildfire that burned at lower intensity, had slow progression related to moist fuels from heavy rains in the area earlier that year, and yielded positive resource benefits.

One alternative hypothetical scenario for the Rough Fire (Scenario 1) consists of a smaller Rough Fire under the assumption that a planned prescribed fire (Boulder Creek Unit 1 prescribed fire unit), which did not occur, had occurred prior to the Rough Fire. This smaller fire hypothetical scenario assumes that when the Rough Fire got to the area of the Boulder Creek Unit 1 prescribed fire unit, progression downslope toward the Central Valley of California would have stopped. Fire perimeters are shown for the Rough Fire, Sheep Complex Fire, and Boulder Creek Unit 1 Prescribed Fire area in Figure 5-4.

Another hypothetical scenario for the Rough Fire (Scenario 2) was a larger fire that progressed through the area of the Sheep Complex Fire with an assumption that fuels were dry and fuel loading would be similar to the surrounding area as if the Sheep Complex Fire had not happened. The hypothetical larger Rough Fire includes the actual Rough Fire in addition to the area of the Sheep Complex Fire. The hypothetical wildfire version of the Sheep Complex Fire was based on the original spatial extent of the Sheep Complex Fire. The Sheep Complex Fire activity data was aggregated to the total event/fuelbed/location, then a daily fraction of total acres from the Rough Fire (from September 1 to 10, 2015) to the Sheep Complex Fire aggregated activity data was applied to each of these combined factors. This means that the Sheep Complex Fire kept the same total area and fuel beds but was temporalized like the Rough Fire activity between September 1 and 10, 2015. This allowed the Sheep Complex area to be burned as part of the Rough Fire at the point the actual Rough Fire progressed to this area and beyond.

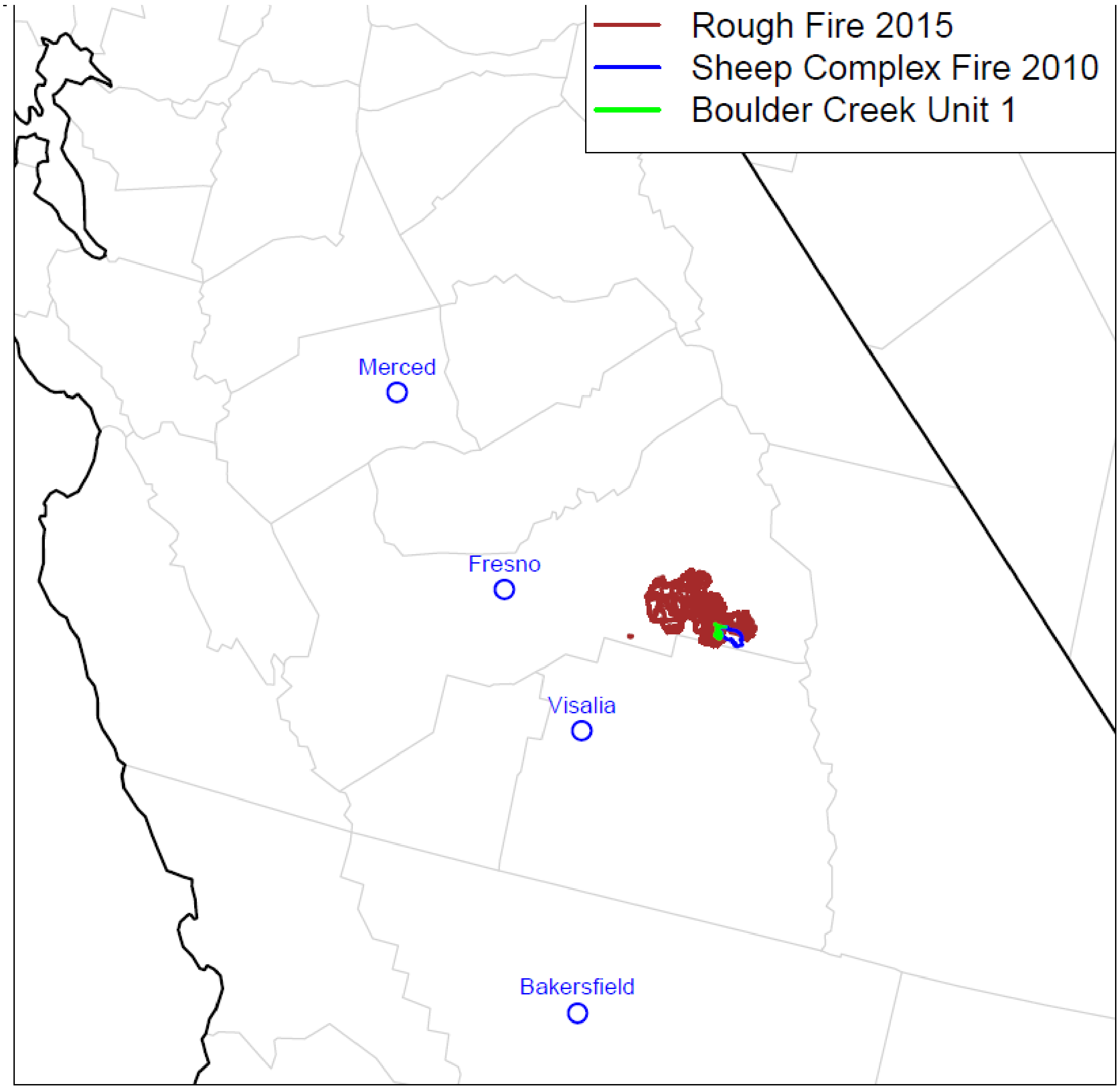
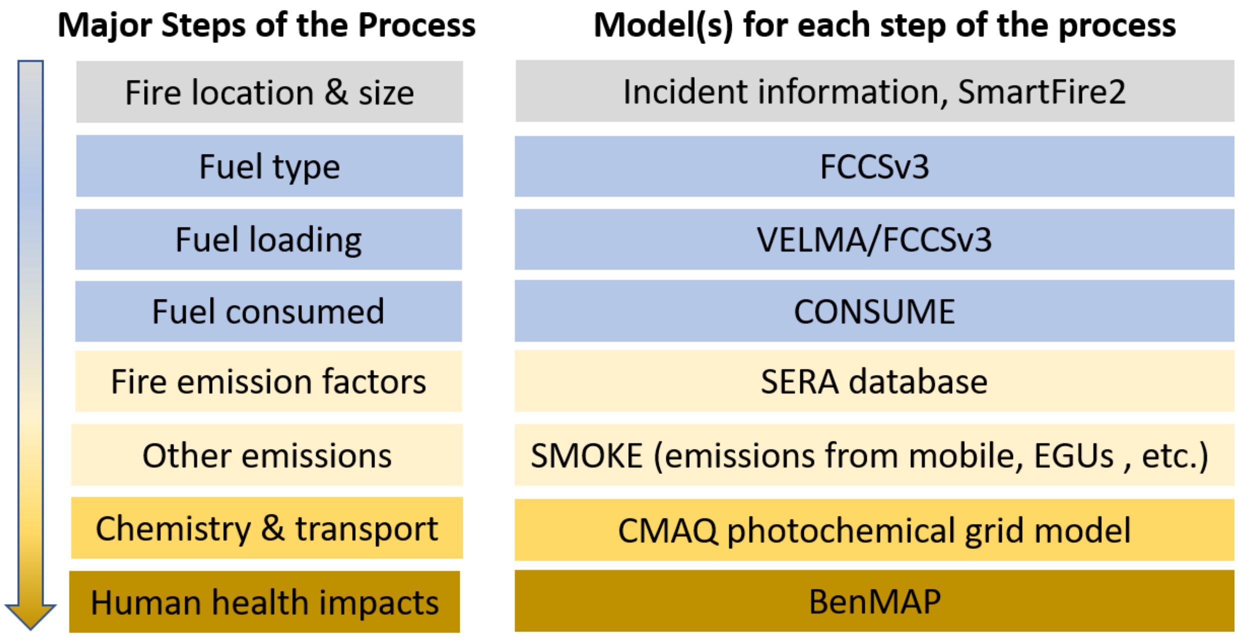



**Figure 5-4** **Schematic showing the 2015 Rough Fire, 2010 Sheep Complex Fire, and Boulder Creek Unit 1 prescribed burn unit in relation to large urban areas in central California.**

A prescribed fire (Boulder Creek Unit 1) was originally planned for an area adjacent to the footprint of the Sheep Complex 2010 fire in 2013. This planned prescribed fire represents the minimum amount of prescribed fire activity that was needed to create the suppression anchor that underpins the smaller hypothetical scenario (Scenario 1) as the initial prescription plan for the area called for approximately 5 more years of prescribed fire activity in the area (USFS, 2014). Boulder Creek Unit 1included a 3,200-acre area that was intended to restore fire and reduce fuels and fire behavior for this steep and inaccessible area of the Boulder Creek drainage, through which the Rough Fire subsequently burned. Since this prescribed fire unit was never burned, a series of days in the fall of 2014 were selected that matched meteorological conditions for a prescribed burn in the area of the Boulder Creek prescribed fire burn unit. September 30 to October 3, 2014 were selected as days matching meteorology appropriate for this prescribed fire burn unit.

## 5.2 Methodology

The air quality surfaces for $PM_{2.5}$ and ozone for the TC6 Fire and Rough Fire, each hypothetical scenario, and the prescribed fires, were produced using the modeling framework detailed in Figure 5-5, which shows the connectivity and relationships between various tools and models used to develop case study fire emissions. Fire location and timing was based on incident information where available and supplemented with data generated by the Satellite Mapping Automated Reanalysis Tool for Fire Incident Reconciliation Version 2 (SmartFire2; [SF2]) tool (Raffuse et al., 2009). SF2 reconciles data from satellite sensors and ground-based reports to use the strengths of both types of data while avoiding double-counting of fires (Larkin et al., 2020; Larkin et al., 2009).




BenMAP = Environmental Benefits Mapping and Analysis Program; CMAQ = Community Multiscale Air Quality; FCCS = Fuel Characteristic Classification System; SERA = Smoke Emissions Reference Application; SMOKE = Sparse Matrix Operator Kernel Emissions; VELMA = Visualizing Ecosystem Land Management Assessments.

**Figure 5-5 Modeling framework used to characterize wildland fire emissions and air quality impacts for case study analyses.**

The BlueSky Pipeline (https://github.com/pnwairfire/bluesky) is a version of the BlueSky Framework rearchitected as a pipeable collection of stand-alone modules. The original BlueSky Framework was Java based whereas the pipeline is based on Python. The BlueSky Pipeline estimates fuel type, fuel loading, fuel consumption, and emissions for each fire. Fuel type is based on the Fuel Characteristic Classification System (FCCS). Fuel loading is based on a combination of FCCS and Visualizing Ecosystem Land Management Assessments (VELMA) model output. Fuel consumption is based on the CONSUME module in the BlueSky Pipeline. BlueSky Pipeline provides daily total emissions of CO, $NO_X$, $SO_2$, $NH_3$, VOC, and primary $PM_{2.5}$ for each wildfire and prescribed fire. Case study fire emission factors are based on the SERA database (Prichard et al., 2020).

Daily emissions were processed for input to the CMAQ photochemical model using the Sparse Matrix Operator Kernel Emissions [SMOKE, https://www.cmascenter.org/smoke/; CMAS (2020)] emissions model, which also provided emissions of other wildland fires, biogenic, and anthropogenic emissions. The CMAQ model uses emissions generated by the SMOKE model and meteorological data generated by the Weather Research and Forecasting (WRF) model to transport and deposit emissions injected to the model and estimate chemical transformation. The output from the photochemical model was processed for input to U.S. EPA’s Environmental Benefits Mapping and Analysis

Program—Community Edition [BenMAP-CE; U.S. EPA (2019a)] to estimate the human health impacts related to specific fire scenarios for each case study fire (see CHAPTER 8). More details about fuels, emissions, and photochemical modeling follow in subsequent sections of this chapter.

### 5.2.1 Fuels (Fuel Characteristic Classification System [FCCS])

The FCCS contains a reference library of wildland fuelbeds that can be used for wildland fire planning and smoke management decisions (Ottmar et al., 2007). The FCCS calculator within the Fuel and Fire Tools [https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft; FERA (2020)] is used to produce a fuel loadings input file for CONSUME v5.0, a fuel consumption module within the BlueSky Pipeline (Prichard et al., 2021).

Although the LANDFIRE system (LF, 2008), contains a FCCS fuelbed layer, it does not include recent small wildfires and prescribed fires. To support emissions trade-offs analyses, we created four separate 30-m FCCS fuelbed raster layers to represent each of the scenarios evaluated in the Timber Crater 6 case study.

To represent prewildfire fuelbed layers for each of the four scenarios, we assigned base FCCS fuelbeds Table A.5 FUELS-1 based on the 2014 LANDFIRE Existing Vegetation Type (EVT) layer (LF, 2014). We then used an existing Python script developed to update the base fuelbeds to represent canopy and surface fuel changes associated with recent wildfires and prescribed burns within the study area, including the 2010 Phoenix and 2014 Founders Day fires Table A.5 FUELS-2. For the TC6 Fire smaller fire scenario (Scenario 1), fuelbeds were assigned to represent a recent prescribed fire over the entire scenario area so that fuel loading would be more like an area post-prescribed fire rather than multiyear fuel buildup. Fuel loading was not similarly modified for the Rough Fire scenarios. A Python script was used to update fuelbeds to recent low-severity prescribed burns immediately post-disturbance (111), recent high-severity wildfires within 0−5 years (132) and older high-severity wildfires within 5−10 years (133).

### 5.2.2 Characterizing Surface Fuel Loads for Use in the BlueSky Pipeline

Surface fuel load characterization is an important component of modeling air quality impacts associated with wildfires and prescribed fires. The most commonly used tool for estimating surface fuel loads in the U.S. is the FCCS (Ottmar et al., 2007), which characterizes available fuel loading for various vegetation classification categories across a landscape and includes both vegetation type (e.g., Ponderosa Pine, Red Alder) and fuel load category (e.g., canopy, shrubs, nonwoody).

While FCCS captures the general diversity of available fuels found throughout the U.S., the fuel loadings are assumed to be homogenous within each vegetation type. Studies suggest that FCCS and other vegetation classification-based approaches do not fully characterize the spatial and temporal variability of fuels, site-specific conditions, and the presence of disturbances such as harvests and prescribed fires (Lutes et al., 2009; Brown and See, 1986, 1981). In light of these considerations, an ecohydrological modeling approach was implemented for this assessment to supplement existing FCCS data, specifically to characterize spatial and temporal variations more fully in forest fuel loads arising from site-specific biophysical and disturbance conditions.

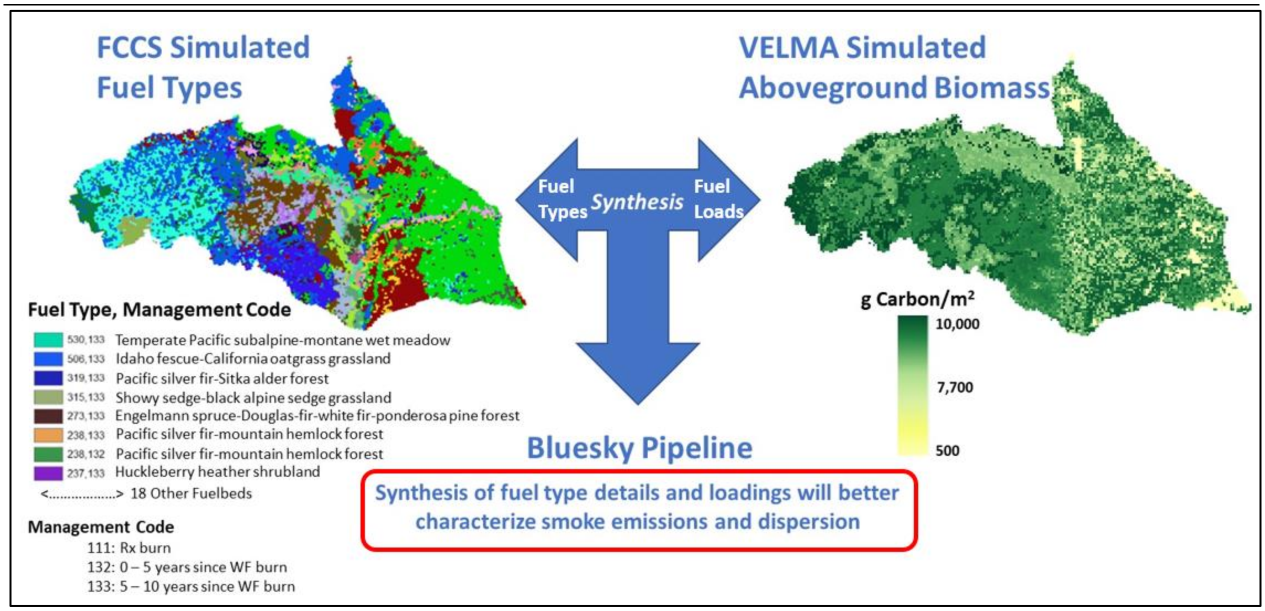
The VELMA model is a spatially distributed (grid-based) ecohydrological model that simulates integrated responses of vegetation, soil, and hydrologic components to various inputs of land use, soil, and climate (McKane et al., 2014). It has been widely applied to many terrestrial ecosystem types, including forests, grasslands, agricultural floodplains, and alpine and urban landscapes. Particularly in western U.S. forests and grasslands, VELMA has simulated effects of fire and harvest and subsequent spatial and temporal dynamics of ecosystem recovery (McKane et al., 2020; Yee et al., 2017; Barnhart et al., 2015; Abdelnour et al., 2013; Abdelnour et al., 2011).

VELMA was used here to simulate aboveground biomass for the two case study fires (i.e., the TC6 Fire in Oregon and the Rough Fire in California). In addition, for the Rough Fire case study VELMA modeling was conducted for additional fires within the actual Rough Fire vicinity to support the development of hypothetical scenarios. This additional modeling included the areas of the Sheep Complex Fire and the area within the proposed Boulder Creek prescribed fire. More detailed information on the actual and hypothetical fuel treatments and boundaries are described in CHAPTER 3 and in the present chapter. For each case study area, VELMA was spatially initialized using high-resolution (30-m), aboveground total (live and dead) biomass developed for western forest ecosystems (California, Oregon, Washington) by the Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) project at Oregon State University (LEMMA, 2020; Kennedy et al., 2018; Davis et al., 2015). LEMMA forest biomass map data are developed and updated annually using state-of-the-science, satellite-based change-detection technology (Landsat), calibrated using the U.S. Forest Service (USFS) Forest Inventory and Analysis (FIA) regional network of forest biomass plot measurements (Bell et al., 2018).

Extensive validation of LEMMA-mapped biomass predictions has previously been performed for the western U.S., including the Deschutes National Forest near the TC6 case study area (Bell et al., 2018). In validation tests, LEMMA-initialized VELMA TC6 application closely simulated aboveground biomass pools and rates of accumulation published for this dry coniferous forest ecoregion (Smithwick et al., 2002). This is important because VELMA was initialized for the 2018 TC6 Fire based on 2010 LEMMA biomass data, primarily to allow for potential future prefire fuel reduction simulation treatments using VELMA. The LEMMA aboveground live and dead forest biomass data for the Sheep Complex and Rough fires corresponded to the actual 5 years, 2010 and 2015, respectively. See APPENDIX for details.

Following initialization for each case study site, VELMA's LEMMA-based overstory fuel-load estimates were merged with FCCS surface fuel load estimates, specifically to replace FCCS forest overstory fuel load estimates assumed to be homogenous within each vegetation type, rather than on location-specific data (Lutes et al., 2009; Brown and See, 1986, 1981).

Figure 5-6 generally illustrates how VELMA and FCCS data products were merged and fed into the BlueSky Pipeline. The combined VELMA-FCCS fuelbed database for each site was used as an input to BlueSky Pipeline, specifically to the CONSUME model, to simulate air quality impacts associated with wildfire and prescribed fire simulations. The resulting BlueSky Pipeline input data comprised a raster map of fuelbed classifications and a comma-separated-value (CSV) look-up file of fuel loadings for various fuelbed categories (e.g., canopy, shrubs, nonwoody vegetation, woody fuels, litter/lichen/moss, ground fuels) that include merged FCCS and VELMA fuel type and fuel load data, respectively. The combined use of FCCS and VELMA for this purpose plays to the strengths of both models, together representing the best available science for estimating fine-scale horizontal and vertical distributions of fuelbed types and loadings (Bell et al., 2018; Ottmar et al., 2007).




FCCS = Fuel Characteristic Classification System; g Carbon/m$^2$ = grams carbon per square meter; Rx = prescribed burn; VELMA = Visualizing Ecosystem Land Management Assessments; WF = wildland fire.

Note: Example shown is for the Timber Crater 6 (TC6) Fire case study in Oregon.

**Figure 5-6 Fuel Characteristic Classification System (FCCS) fuel type data and Visualizing Ecosystem Land Management Assessments (VELMA) fuel load data were merged to produce fuelbed inputs for the BlueSky Pipeline.**

In summary, whereas FCCS performs well at providing estimates of management-sensitive surface and understory fuel types and loads, VELMA performs well at estimating overstory/canopy fuel loads by virtue of its use of LEMMA initialization and mechanistically modeled live and dead biomass dynamics. Additional details on the methods used to develop LEMMA-initialized VELMA for both case studies and associated VELMA-FCCS fuelbed databases are located in the Appendix (see Section A.5).

### 5.2.3 Fuel Consumption and Fire Emissions (BlueSky Pipeline)

The BlueSky Pipeline Version 4.2.14 was used support this project. The BlueSky Pipeline is a set of python-based stand-alone modules that can be linked or piped together in a series so that the output of one module becomes the input of the next. For all the fire emission scenarios, the BlueSky Pipeline was used to calculate consumption, to calculate emission factors and to calculate emissions using geo-references area burned input. Generally, as fire data flow through the modules within the BlueSky Pipeline, the modules add to the data without modifying what was already defined. The consumption module used was CONSUME Version 5.0.2. Fuel loadings were based on either FCCS v3 with LandFire v1.4 fuel beds or FCCS v4 with USFS fuel beds. Emissions were based on University of Washington SERA emission factors for the case study fires and Fire Emission Production Simulator (FEPS) v2 for all other fires.

#### 5.2.3.1 Temporal Profile for Timber Crater 6 (TC6) Fire

Fire hotspot characterization data from the Geostationary Operational Environmental Satellite (GOES)-16 Advanced Baseline Imager (ABI) were obtained in Network Common Data Form (NetCDF) format from Amazon's AWS S3 file system at s3://noaa-goes16/ABI-L2-FDCC/2018/ (GOES-R Algorithm Working Group, 2018). The data set comprises latitude, longitude, fire radiative power (FRP), estimated fire area, fire temperature, and a data quality factor (DQF) for each pixel. The fire data are derived (i.e., not directly measured) products of the GOES–ABI. The algorithms for deriving fire data and data quality are described elsewhere (Schmidt et al., 2013). Data from 15−29 July 2018 were extracted from within a bounding box defined by the points (43.03°N, 122.1°W) and (43.1°N, 121.9°W), centered roughly on the centroid of the final Timber Crater 6 Fire perimeter. Although data are typically available at 5-minute intervals, there are often large temporal discontinuities due to absence of detection because of issues such as low fire power, glare or obscuration by smoke or clouds. After filtering for validity (DQF = 0), 166 data points were available for the analysis. Analysis was performed using Python 3 code and libraries.

Fire radiative power is proportional to the rate of fuel consumption in wildland fires (Kremens et al., 2012). To derive a characteristic fuel consumption curve, valid FRP values from all days in the data set were binned by hour. A mean value and standard deviation of FRP was calculated for each hour. Valid detections were available for only the hours 11:00 a.m. to 9:00 p.m. PDT each day over the time span of the fire. It is possible that fire radiative powers were too low and/or weather conditions were not favorable for detections outside of that range of times. A Weibull-like curve function (Barnett, 2002) was fitted to the hourly mean FRP values using the "curve_fit" method from the SciPy (Version 1.4.1) Optimize library. To facilitate curve fitting, mean FRP values outside of the available time range were extrapolated using a linear ramp between the end values (Numpy v.1.18.5 "pad" function).

The resulting fitted curve gives a realistic profile of diurnal fuel consumption and indicates that, on average, peak FRP, and therefore fuel consumption, occurred around 3:00 p.m. PDT. However, the FRP curves for any given day of the fire varied considerably from the fitted curve, as indicated by the large variations in FRP during the afternoon hours. As important, with only 166 data points there is a relative paucity of GOES satellite data for this fire, suggesting that the resulting consumption curve should be used with caution.

#### 5.2.4 Pile/Slash Burn Emissions

Typical practices for collecting fuel leftover from mechanical thinning operations include collecting the debris into three types of piles: machine landing piles (largest), machine grappling piles, and hand piles (smallest). Each of these practices are common at Crater Lake National Park and surrounding areas. Typical geometry for each was provided by land managers in the region (shown in Table 5-1).

**Table 5-1 Emissions and fuel consumption for three different types of slash/pile burn fuel geometry assumptions for the Timber Crater 6 (TC6) case study area.**

| File Name | Geometry | $NO_X$ (tons) | $PM_{2.5}$ (tons) | VOC (tons) | CO (tons) | $NH_3$ (tons) | $SO_2$ (tons) | Fuel Consumption (tons) |
|---|---|---|---|---|---|---|---|---|
| Machine landing pile | 50′ × 100′ × 25′ | 0.6256 | 2.1475 | 0.7200 | 12.0854 | 0.5942 | 0.3118 | 270.4 |
| Machine grappled pile | 15′ × 15′ × 10′ | 0.0113 | 0.0387 | 0.0130 | 0.2175 | 0.0107 | 0.0056 | 4.9 |
| Hand_pile | 5′ × 5′ × 5′ | 0.0004 | 0.0014 | 0.0005 | 0.0082 | 0.0004 | 0.0002 | 0.2 |

CO = carbon monoxide; $NH_3$ = ammonia; $NO_X$ = nitrogen oxides; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; $SO_2$ = sulfur dioxide; VOC = volatile organic compound.

Pile burn emissions were based on the University of Washington (UW) tool [https://depts.washington.edu/nwfire/piles/ University of Washington (2014)]. This tool provides daily emissions of $PM_{2.5}$, CO, and VOC (also provides $CO_2$ and $CH_4$ which were not used in this analysis). The CMAQ model needs emissions for $NO_X$, $NH_3$, and $SO_2$, and these were estimated using BlueSky Pipeline FEPS assuming a 70/15/15 flaming/smoldering/residual smoldering split for pile burns. A cubic shape was assumed for each pile. Pile burns used the same diurnal profile as prescribed fire (late morning start and ending in the early evening).

### 5.2.5 Air Quality Modeling System

The CMAQ Version 5.3.2 model was applied with aqueous phase chemistry (Fahey et al., 2017), inorganic thermodynamics (Fountoukis and Nenes, 2007), and gas phase chemistry based on the Carbon Bond 6 Revision 3 mechanism (Emery et al., 2015). The default option was used where photolysis rates were attenuated in the presence of model predicted particulate matter (Baker et al., 2016). Secondary organic aerosol (SOA) treatment is a yield-based approach based on precursors including isoprene, monoterpenes, sesquiterpenes, benzene, toluene, and xylenes. Some of the SOA becomes nonvolatile through oligomerization processes (Carlton et al., 2010). Primarily emitted organic aerosol is treated as nonvolatile. The ratio of organic mass to organic carbon is assumed to be 1.7 for primary $PM_{2.5}$ wildland fire emissions (Simon and Bhave, 2012).

The WRF model was used to provide the modeling system meteorological inputs (Skamarock et al., 2008). Both CMAQ and WRF were applied with 35 layers to represent the vertical atmosphere from the surface up to 50 mb. The WRF configuration used here has been evaluated and shown reasonable performance for winds, temperature, and surface mixing layer height for the Pacific Northwest (Zhou et al., 2018) and California (Baker et al., 2013). WRF was initialized with the 12-km North American mesoscale (NAM) analysis product [https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-mesoscale-forecast-system-nam; NCEP (2021)]. CMAQ initialization and boundary inflow conditions were extracted from coarser hemispheric CMAQ simulations.

Anthropogenic emissions in the model domain were based on the 2016 National Emission Inventory (U.S. EPA, 2019b) with year-specific data used for electrical generating units based on continuous emissions monitor data. Biogenic emissions were estimated with the Biogenic Emission Inventory System Version 3.6.1, which has been shown to perform well for biogenic VOC in California (Bash et al., 2016). Emissions of wildland fires other than the case studies were based on daily fire location and burn area information using the SmartFire2 system, which is largely based on satellite products and incident information. Location, burn area, and date information is provided to the BlueSky Pipeline to estimate fuel type, fuel moisture, and fuel consumption that is used to estimate daily emissions (Urbanski, 2014) of CO, $NO_X$, VOC, $SO_2$, $NH_3$, and $PM_{2.5}$ based on FEPSv2 emission factors for each noncase study wildfire and prescribed fire in the model domain (Larkin et al., 2020).

SMOKE is used to apply a fire type-specific diurnal profile and allocates total emissions of $NO_X$, VOC, and $PM_{2.5}$ to specific model species needed for chemical mechanisms. Speciation profiles are based on those available in the SPECIATE database [https://www.epa.gov/air-emissions-modeling/speciate; U.S. EPA (2020b)]. $NO_X$ emissions were allocated 10% to NO and 90% to $NO_2$. Speciation profiles for VOC and primarily emitted $PM_{2.5}$ are provided in Table A.5 SPECIATION-1. Daily total emissions were allocated to specific hours of the day based on default profiles for wildfire and prescribed fire (Baker et al., 2020; Baker et al., 2016). Fuel moisture is a global parameter that only varies by fire type (wildfire or prescribed).

## 5.3 Results—Case Studies

For both the Timber Crater 6 and Rough Fire case studies total acres burned, $PM_{2.5}$ emissions, fuel, and fuel consumption are shown for the wildfire, alternative hypothetical scenarios, and areas that had been managed in the past in Table 5-2.

Photochemical model predictions of baseline maximum daily 8-hour average (MDA8) $O_3$ and major components of speciated $PM_{2.5}$ (total carbon, sulfate ion, and nitrate ion) were paired in time and space with measurements from routine surface network monitors. This type of comparison provides information about how well the modeling system is predicting air quality from wildland fire and other sources. A reasonable representation of the chemical environment surrounding fire plumes is important to best capture secondarily formed pollutants like $O_3$ since wildland fire emit precursors of $O_3$ ($NO_X$ and VOC) that can react with other sources of pollution to form $O_3$.

The photochemical modeling system generally compares well with ambient data for the various episodes included in this assessment. Model performance metrics for daily model-observation pairs at routine surface network monitors aggregated over each episode are shown in Table A.5-1. Each prediction-observation pair is also shown with scatterplots for each species (Figure A.5 MPE-1 to Figure A.5 MPE-6). Additional model performance information is provided as part of subsequent figures in this section that show episode average surface level modeled $PM_{2.5}$ and MDA8 $O_3$ compared with measurements made at routine monitors. The modeling system does well at replicating spatial gradients in $PM_{2.5}$ and $O_3$. It also generally captures synoptic and day-to-day variability in measurements near each of the case study fires. The performance metrics for these episodes is consistent with the performance shown for this type of modeling system for monitors impacted by large wildfires in the western U.S. (Baker et al., 2018; Koplitz et al., 2018; Baker et al., 2016). Very little data exist on episodic model performance for these areas during large wildfire events for performance comparison. However, performance metrics of other studies completed over longer time frames and larger model domains are generally consistent with those estimated for the modeling periods included in this assessment (Kelly et al., 2019; Simon et al., 2012).

## Table 5-2 Wildfire and prescribed fires modeled as part of the Timber Crater 6 (TC6) and Rough Fire case studies.

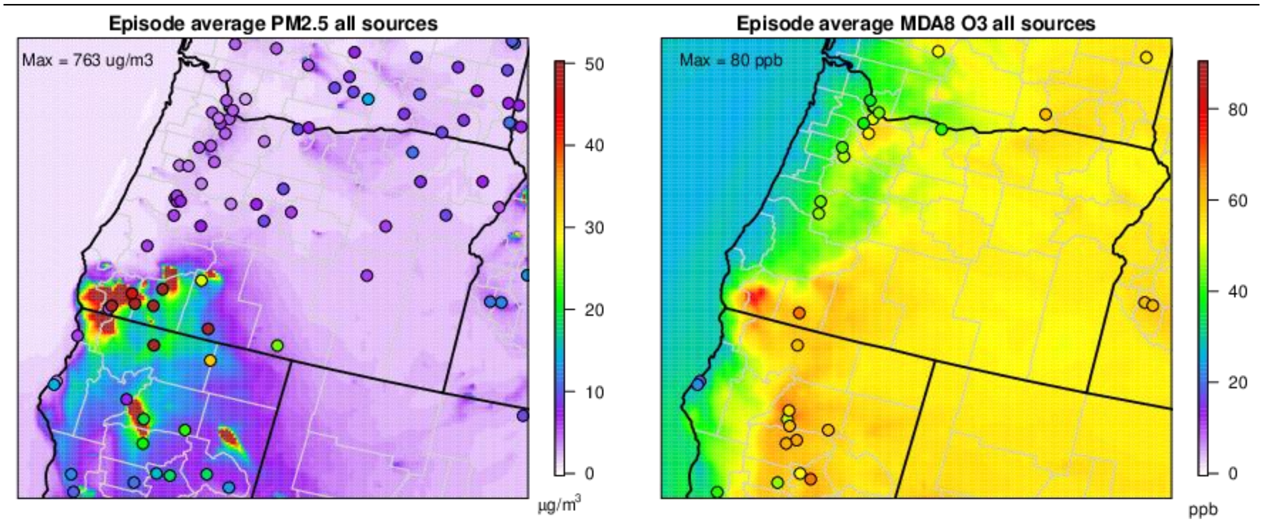
| Fire/Burn Unit Name | Type | Modeled Time Period | Acres Burned (acres) | Total Fuel Consumption (tons) | Total Fuel (tons) | $PM_{2.5}$ Emissions (tons) |
|---|---|---|---|---|---|---|
| Timber Crater 6 | Actual wildfire | July 15 to 31, 2018 | 3,123 | 213,454 | 145,985 | 1,869 |
| TC6 hypothetical smaller fire (1) | Hypothetical wildfire | July 15 to 31, 2018 | 1,237 | 37,954 | 91,419 | 1,041 |
| TC6 hypothetical larger fire (2a) | Hypothetical wildfire | July 15 to 31, 2018 | 20,878 | 468,843 | 1,249,089 | 12,794 |
| TC6 hypothetical larger fire (2b) | Hypothetical wildfire | July 15 to 31, 2018 | 27,373 | 727,180 | 1,825,606 | 20,015 |
| Timber Crater 1978 | Hypothetical prescribed fire | September 1 to 30, 2019 | 2,049 | 26,992 | 112,362 | 565 |
| Cornerstone | Hypothetical prescribed fire | September 1 to 30, 2019 | 772 | 10,671 | 69,787 | 232 |
| Timber Crater 1/2 | Hypothetical prescribed fire | September 1 to 30, 2019 | 633 | 7,751 | 37,649 | 157 |
| 2019 actual prescribed fires | Actual prescribed fire | September 1 to 30, 2019 | 886 | 6,206 | 20,955 | 117 |
| Rough Fire | Actual fire | August 1 to September 30, 2015 | 145,438 | 3,284,638 | 7,128,199 | 85,638 |
| Rough hypothetical smaller fire (1) | Hypothetical wildfire | August 1 to September 30, 2015 | 113,349 | 2,631,258 | 6,450,696 | 68,949 |
| Rough hypothetical larger fire (2) | Hypothetical wildfire | August 1 to September 30, 2015 | 154,354 | 3,448,094 | 7,562,392 | 89,349 |
| Boulder Creek Unit 1 | Hypothetical prescribed fire | September 26 to October 7, 2014 | 3,289 | 30,163 | 90,452 | 499 |
| Sheep Complex Fire | Actual fire | July 30 to September 30, 2010 | 8,916 | 103,037 | 434,193 | 2,344 |

$PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

### 5.3.1 Timber Crater 6 (TC6) Air Quality Impacts

A domain with 4-km-sized grid cells covering Oregon and northern California were applied for the time period coinciding with the case study fire (July 2018). Initial conditions and boundary inflow were extracted from a CMAQ simulation for a 12-km domain covering the continental U.S. for the entire year of 2018.

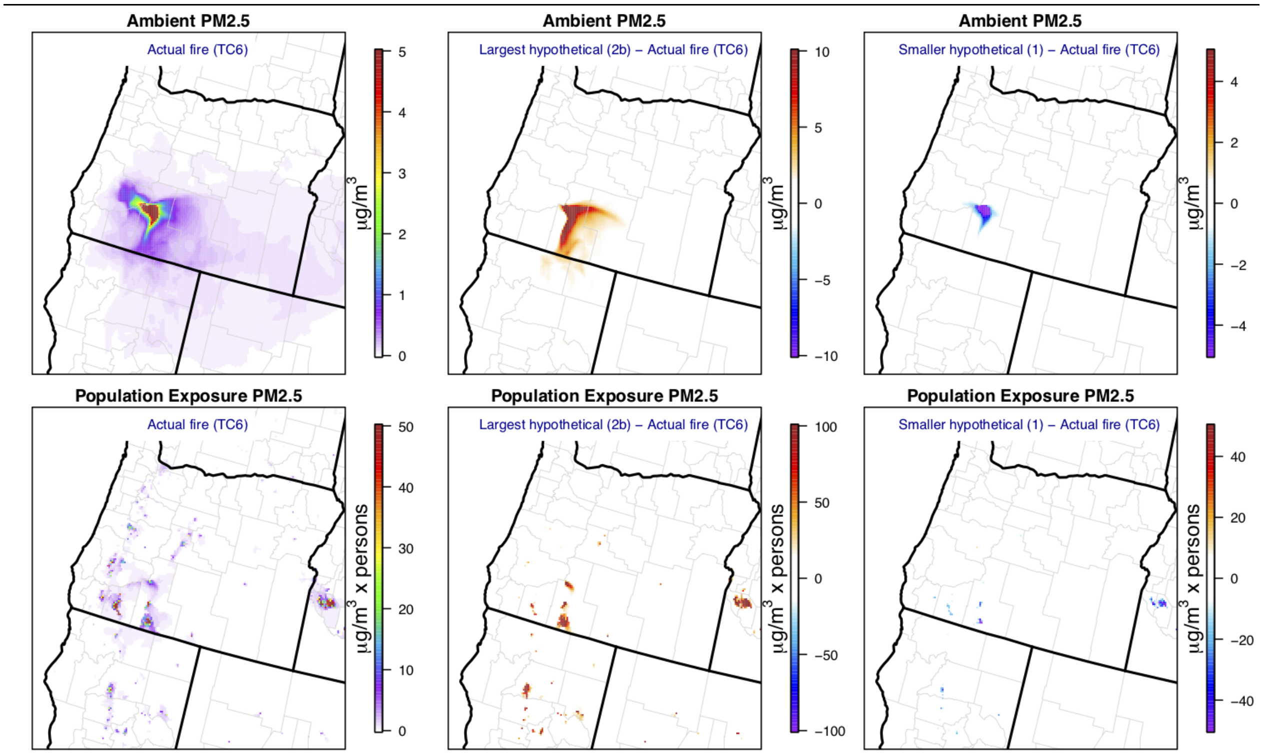
Model predicted episode average $PM_{2.5}$ and MDA8 $O_3$ for the 2018 episode compared well with routine surface monitor data (Figure 5-7). Large wildfires in southwest Oregon and northern California resulted in a strong gradient in $PM_{2.5}$ concentrations across the domain. Enhancements of $O_3$ from wildfire were less evident because meteorologic conditions during this period was favorable to regional formation. Agreement between model predictions and measurements provides confidence that the actual and hypothetical case study fires are being modeled in a realistic chemical and physical environment.




Max = maximum; MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $O_3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; ppb = parts per billion.

**Figure 5-7 Episode average $PM_{2.5}$ and maximum daily 8-hour average (MDA8) ozone ($O_3$) predicted by the modeling system and measured by routine surface monitors for the 2018 modeling period used for the Timber Crater 6 (TC6) scenarios.**

Episode average model predicted $PM_{2.5}$ from the actual TC6 Fire and hypothetical scenarios are shown in Figure 5-8 (top row). To assess population exposure to $PM_{2.5}$ produced by the TC6 Fire, model predictions were also multiplied by gridded population to provide an estimate of aggregate population exposure (Figure 5-8, bottom row). Figure 5-8 also shows the difference in episode average $PM_{2.5}$ between the largest and smallest hypothetical scenarios and the actual fire scenario. The spatial pattern of differences between the largest hypothetical scenario (2b) and the actual TC6 Fire is strongly influenced by days toward the end of the largest hypothetical fire scenario where nighttime winds blew smoke southward toward the Oregon-California border. The spatial extent of impacts from the hypothetical scenario 2a fire (not shown) are similar to hypothetical scenario 2b, but with a smaller magnitude of change.

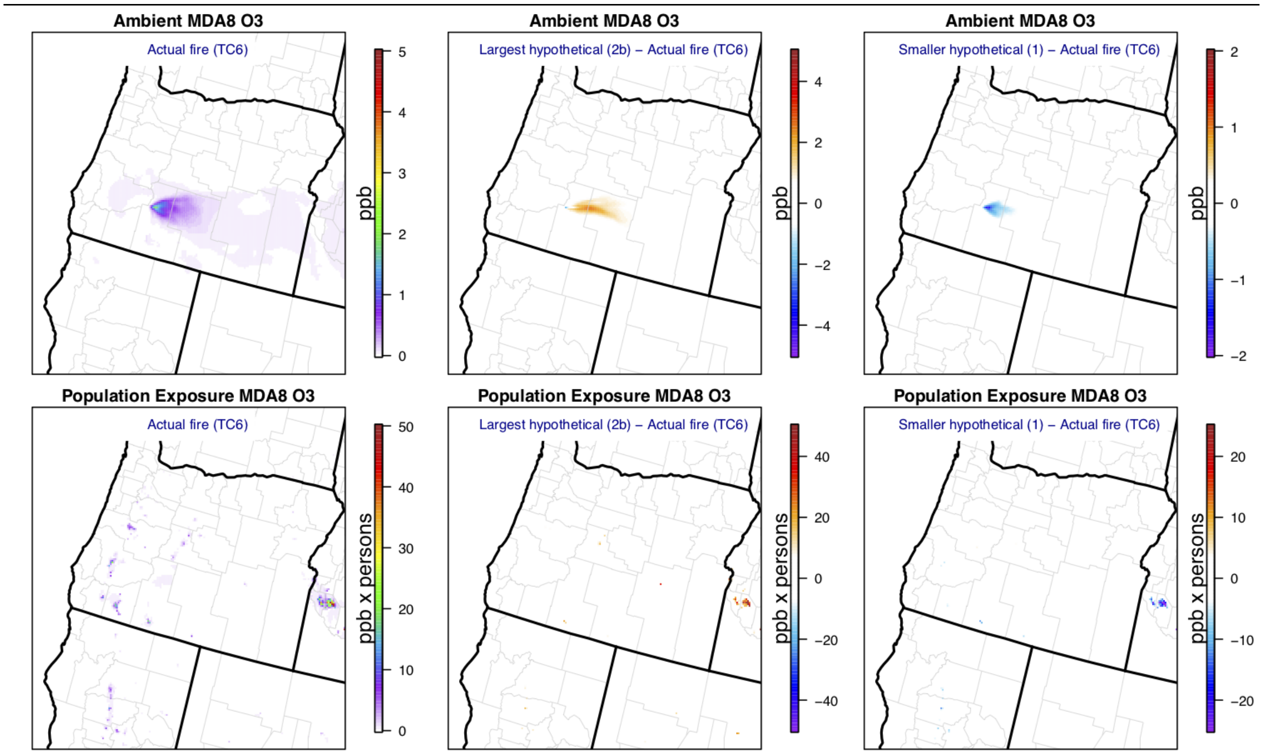



$PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6; µg/m$^3$ = micrograms per cubic meter.

Note: Ambient $PM_{2.5}$ impacts are shown in the top row and aggregate population exposure in the bottom row where $PM_{2.5}$ is multiplied by gridded population.

**Figure 5-8 Episode average $PM_{2.5}$ impacts and aggregate population exposure from the actual Timber Crater 6 (TC6) Fire and the difference between the actual fire and largest (2b) and smaller (1) hypothetical scenarios.**

The Episode average model predicted MDA8 $O_3$ from the TC6 Fire and hypothetical Scenarios 1 and 2b are shown in Figure 5-9 (top row). Model predictions are also multiplied by gridded population to provide an estimate of aggregated population impacts. The spatial pattern of differences between the largest (2b) and actual scenario is strongly influenced by daytime winds blowing smoke eastward toward the Oregon-Idaho border. This differs from the spatial extent of $PM_{2.5}$ impacts because the largest $PM_{2.5}$ concentrations are overnight when winds moved air toward the south. Impacts of the daytime wind patterns dominate the spatial extent of $O_3$ formation because these daytime winds coincide with solar radiation, which is needed for photochemical $O_3$ production.




MDA8 = maximum daily 8-hour average; $O_3$ = ozone; ppb = parts per billion; TC6 = Timber Crater 6.

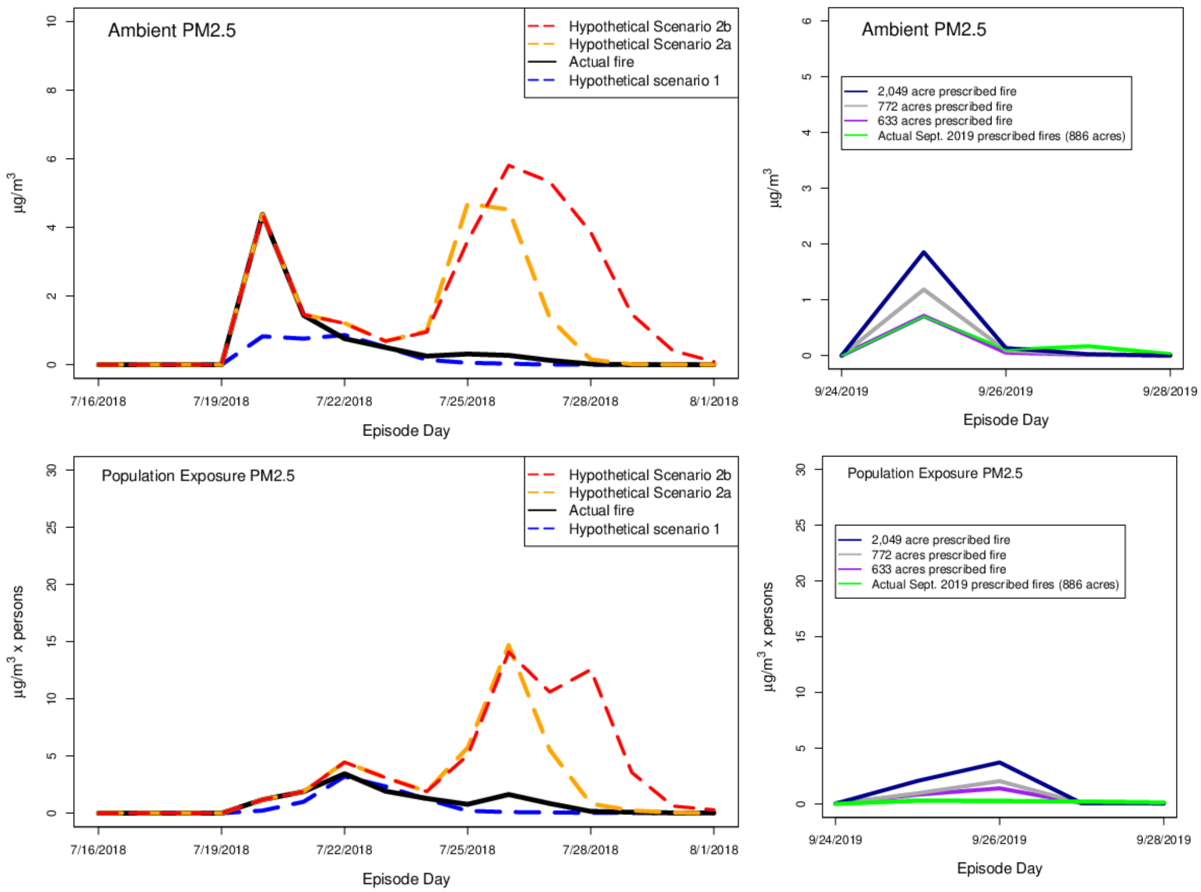
Note: Ambient MDA8 $O_3$ impacts are shown in the top row and aggregate population exposure in the bottom row where MDA8 $O_3$ is multiplied by gridded population.

**Figure 5-9 Episode average maximum daily 8-hour average (MDA8) ozone ($O_3$) impacts and aggregate population exposure from the actual Timber Crater 6 (TC6) Fire and the difference between the actual fire and largest (2b) and smaller (1) hypothetical scenarios.**

Without considering air quality impacts, based on this case study and other similar studies, results indicate that land management, such as prescribed fire and mechanical thinning, reduce fuel, which means less fuel is consumed when wildfires happen later. Less fuel available for wildfire consumption in turn means less emissions and lower levels of downwind pollutants. Reduced fuel loading also can lead to smaller fire perimeters, which is represented in the smaller fire hypothetical (Scenario 1) presented here.

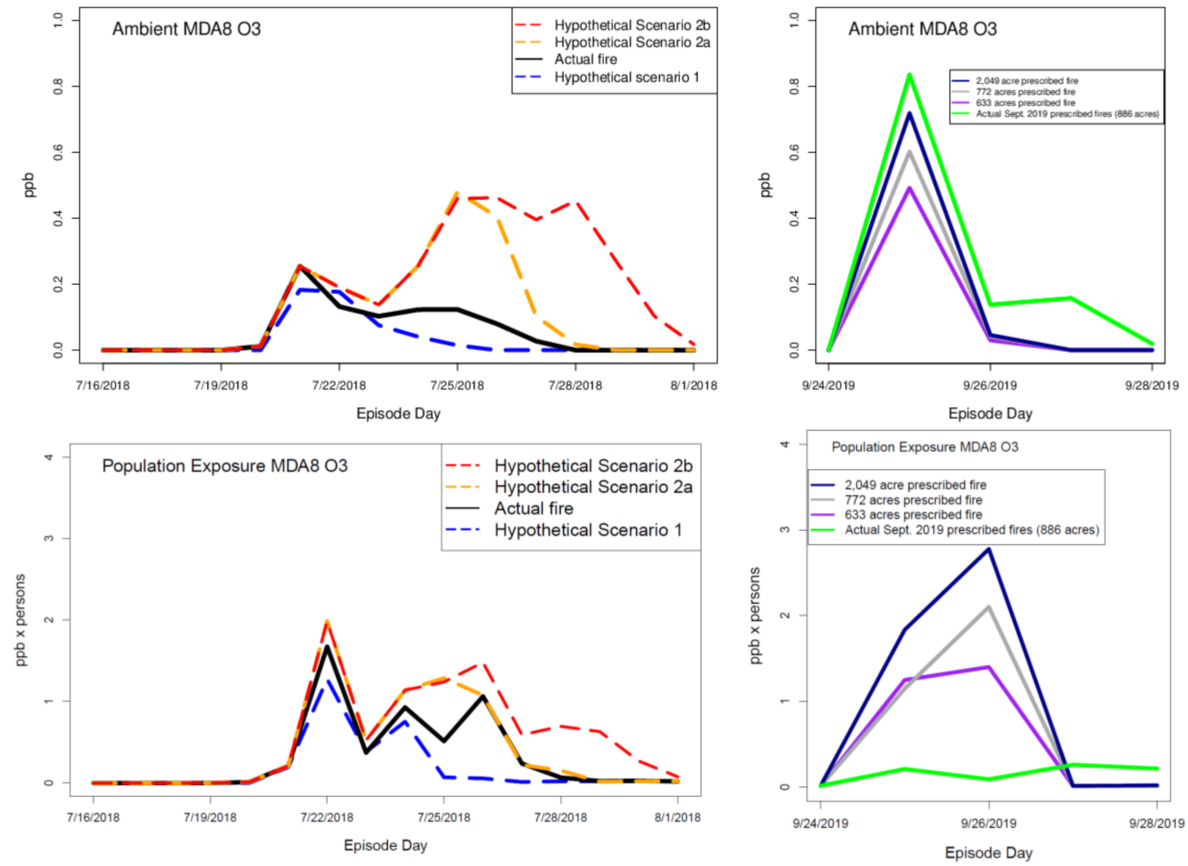
This smaller perimeter is based on expert judgement for this hypothetical scenario and is not based on fire behavior or fire spread models. Illustrating the change in air quality related to past land management activity is challenging because spatial and temporal scales of both are quite different. For instance, many prescribed fires may need to be conducted over many years to effectively minimize the rate of spread of wildfire or reduce fuels enough to impact air quality. Further, only a single period of conducive meteorology (September 2019) was used for the prescribed fire impacts, which does not capture the variability possible if other years or time of year were chosen.

Figure 5-10 shows daily domain average $PM_{2.5}$ ambient and aggregate population exposure from the actual TC6 Fire and hypothetical fire scenarios compared with multiple prescribed fires. All the prescribed fires were modeled in separate simulations with the same days in September 2019 when prescribed fires were happening near Crater Lake National Park. Similar information is shown for MDA8 $O_3$ in Figure 5-11. The daily average impacts only include grid cell-days where modeled fire impacts exceed a threshold (0.01 $\mu g/m^3$ for $PM_{2.5}$ and 0.01 ppb for MDA8 $O_3$) so that the average does not include large areas of the model domain with no fire impacts due to wind transport patterns.




μg/m³ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm.

**Figure 5-10 Daily average $PM_{2.5}$ ambient (top row) impacts and estimates of aggregate population exposure (bottom row) from the Timber Crater 6 (TC6) case study scenarios (left) and prescribed fire scenarios (right).**




MDA8 = maximum daily 8-hour average; $O_3$ = ozone; ppb = parts per billion; Rx = prescribed fire..

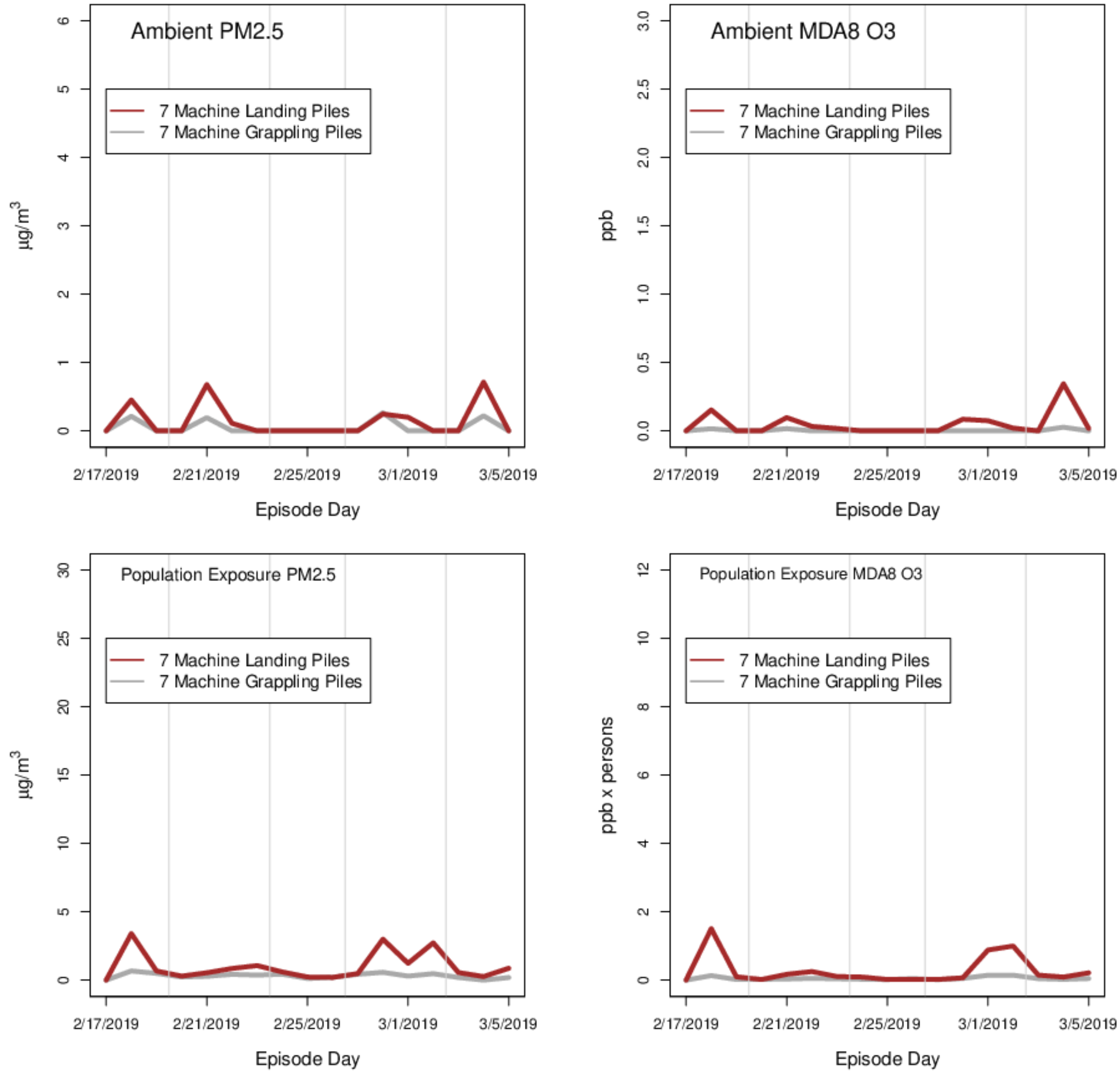
**Figure 5-11 Maximum daily 8-hour average (MDA8) ozone ($O_3$) ambient (top row) impacts and estimates of aggregate population exposure (bottom row) from the Timber Crater 6 (TC6) case study scenarios (left) and prescribed fire scenarios (right).**

Daily aggregate population exposures are notably different than ambient impacts for July 20 when ambient concentrations were high, but winds did not transport smoke to populated areas. The prescribed fires had high ambient impacts but did not impact highly populated areas in this case study. The large estimated population exposures of the biggest hypothetical fires toward the middle and end of the episode are related to larger fire size (e.g., more fuel consumption and emissions) and winds blowing smoke towards populated areas on the additional simulation days.

The daily impacts of prescribed fire on $PM_{2.5}$, particularly the estimated population exposures, were typically lower than wildfire. However, the daily impacts of MDA8 $O_3$ from prescribed fire were sometimes comparable or even larger than the wildfire scenarios. This is due to the large amount of fuel burned as part of the hypothetical prescribed fires on a single day compared to the daily amount of fuel consumed by these small (small compared to the Rough Fire for instance) hypothetical wildfire scenarios.

Further, the prescribed fire emissions are temporally allocated to daytime hours which means more of the mass is available for photochemical reactions leading to $O_3$ production compared to wildfire emissions which are spread out over the entire day and night.

Figure 5-12 shows daily average $PM_{2.5}$ and MDA8 $O_3$ ambient impacts and estimates of aggregate population exposure results from hypothetical slash burn piles in the area of the TC6 Fire. These slash burns were based on common slash burning activity (pile type, size, geometry, and fuel; see Table 5-1). A total of seven hypothetical pile burns were included in each model simulation. These piles were not intended to relate to the amount of fuel from mechanical thinning activity in the area but rather illustrate the potential impacts of slash burning on $PM_{2.5}$ and MDA8 $O_3$ on winter days when meteorology conditions would be conducive for slash burns (e.g., snow cover, no rain, cold temperatures).



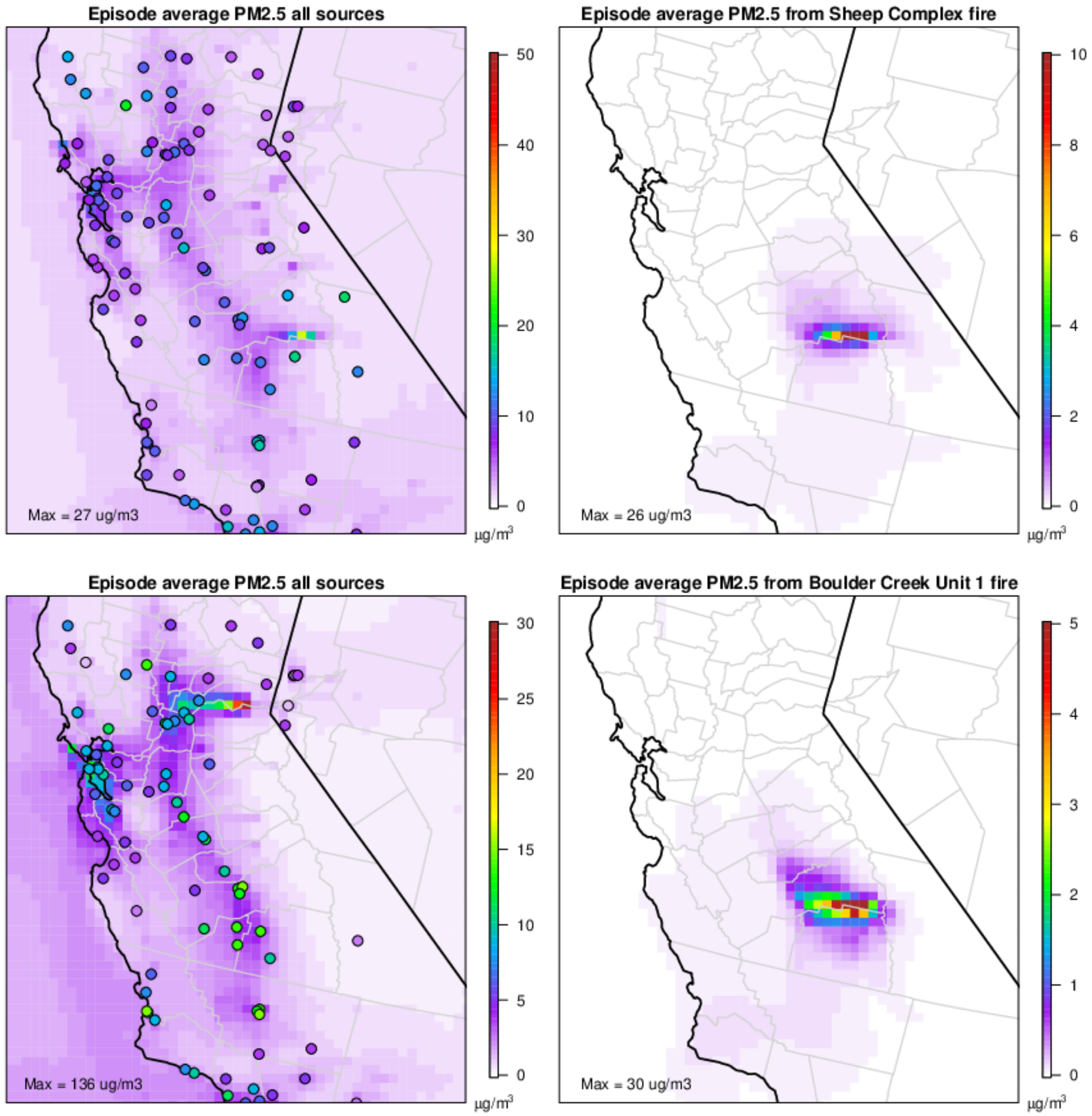

MDO8 = maximum daily 8-hour average; μg/m$^3$ = micrograms per cubic meter; $O_3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; ppb = parts per billion.

**Figure 5-12 Daily average $PM_{2.5}$ (left) and maximum daily 8-hour average (MDA8) ozone ($O_3$) (right) ambient (top row) impacts and estimates of aggregate population exposure (bottom row) from hypothetical pile burns from the Timber Crater 6 (TC6) case study area.**

### 5.3.2 Rough Fire Air Quality Impacts

The modeling system was applied for the 2015 Rough Fire, a hypothetical smaller Rough Fire (Scenario 1), a hypothetical larger Rough Fire (Scenario 2), the 2010 Sheep Complex Fire, and a hypothetical prescribed fire (Boulder Creek Unit 1) for a period matching ideal meteorological conditions for prescribed fire in the fall of 2014. The larger Rough Fire hypothetical (Scenario 2) includes the actual Rough Fire in its entirety and also includes the area of the Sheep Complex Fire, which did not burn as part of the actual Rough Fire. The smaller Rough Fire hypothetical scenario (Scenario 1) eliminates sections of the actual Rough Fire that were downslope of an area planned for prescribed fire (Boulder Creek Unit 1) but never happened. This smaller fire hypothetical is based on the idea that if that prescribed fire had happened before the Rough Fire, it would have provided a boundary for fire suppression and stopped progression after that point downslope toward the Central Valley of California.

CMAQ was applied for a 12-km domain covering the continental U.S. Initial conditions and boundary inflow were extracted from a coarser hemispheric scale photochemical model simulation. This coarser grid spacing scale was selected for the larger Rough Fire case study because a larger domain was used in anticipation of impacts much further downwind than the TC6 Fire case study. Model simulations were done for periods coincident with case study fires in 2010 (Sheep Complex), 2014 (hypothetical Boulder Creek Unit 1), and 2015 (actual Rough Fire). Model predicted episode average $PM_{2.5}$ (Figure 5-13) and MDA8 $O_3$ (Figure 5-14) for each episode compared well with routine surface monitor data. This agreement between model predictions and measurements provides confidence that the actual and hypothetical case study fires are being modeled in a realistic chemical and physical environment.

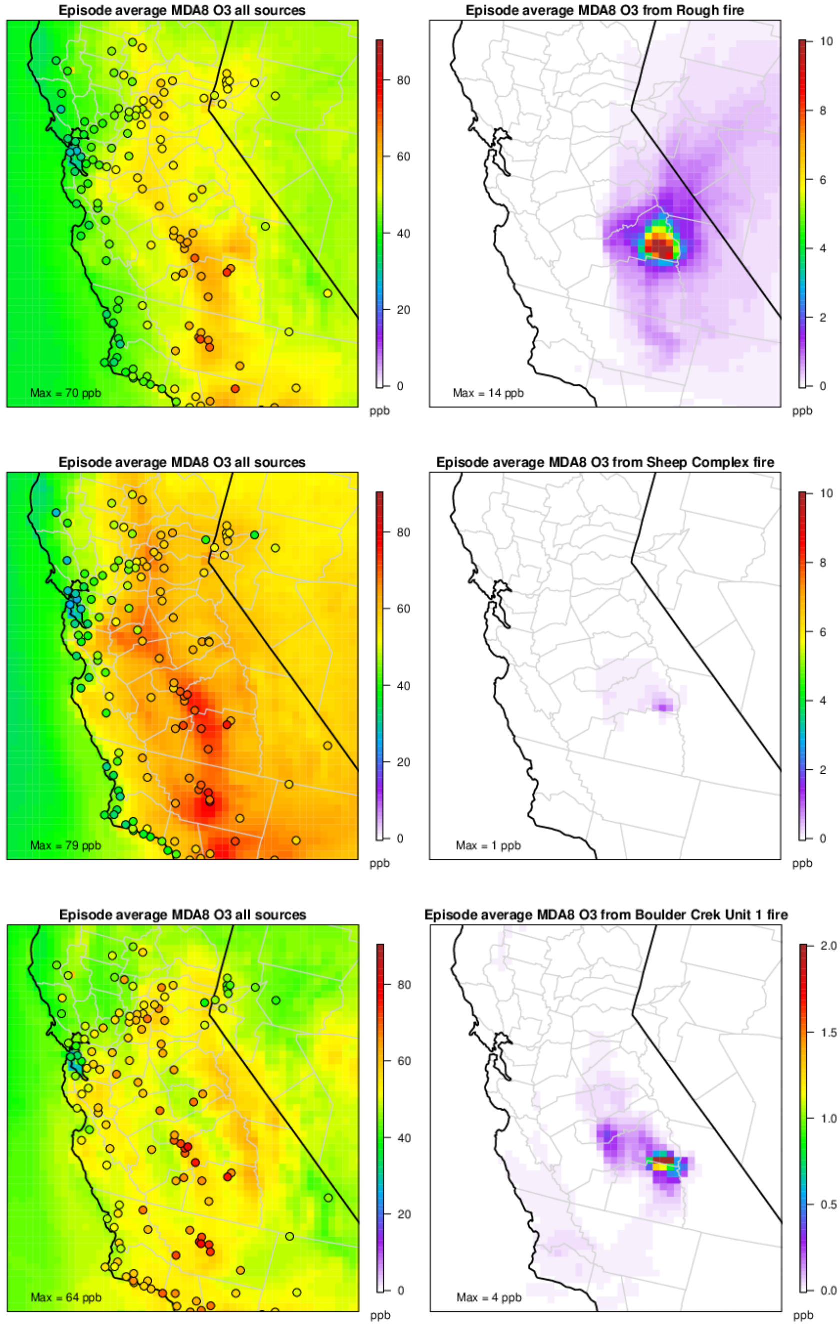



1

2

Max = maximum; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

**Figure 5-13 Episode average $PM_{2.5}$ predicted by the modeling system (from all actual sources) and measured by routine surface monitors (left) and fire specific modeled impacts (right) for the actual Rough Fire (top), actual Sheep Complex Fire (middle), and hypothetical Boulder Creek Unit 1 prescribed fire (bottom).**




Max = maximum; MDA8 = maximum daily 8-hour average; $O_3$ = ozone; ppb = parts per billion.

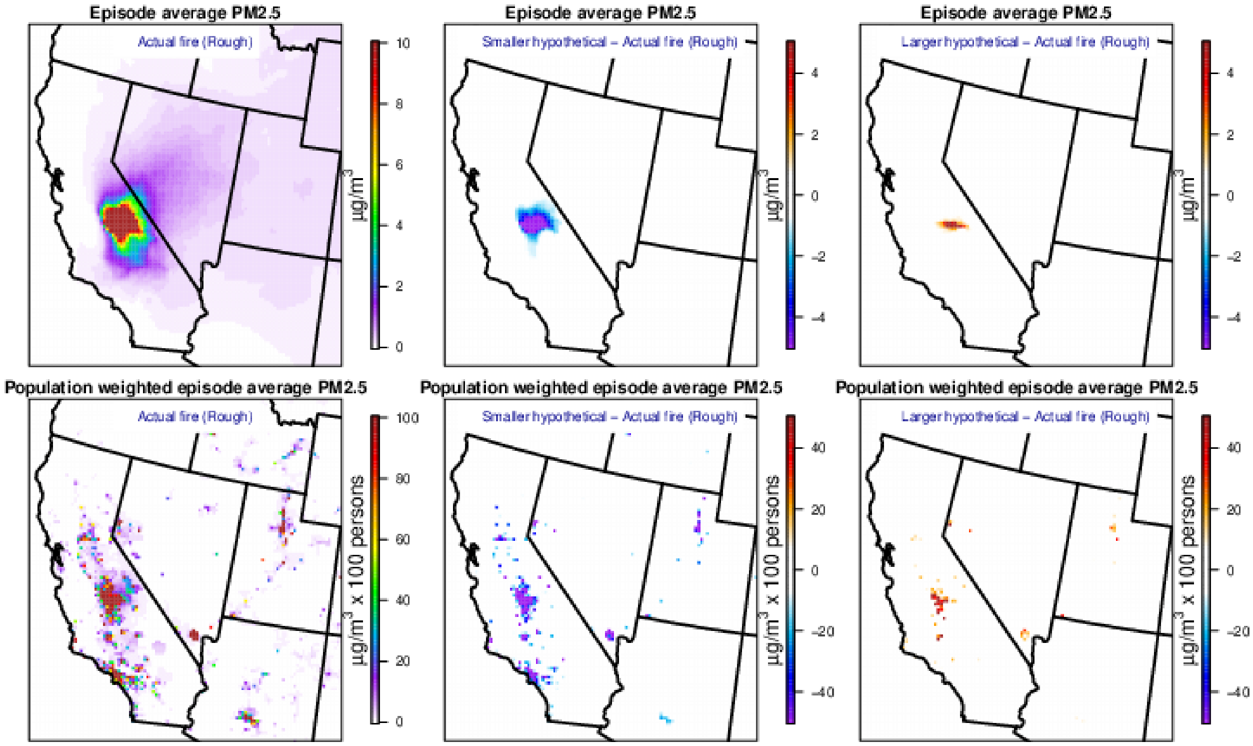
**Figure 5-14 Episode average maximum daily 8-hour average (MDA8) ozone ($O_3$) predicted by the modeling system (from all sources) and measured by routine surface monitors (left) and fire-specific modeled impacts (right) for the 2015 modeling period used for the Rough Fire scenarios (top), 2010 modeling period for the actual Sheep Complex Fire (middle), and 2014 modeling period for the hypothetical Boulder Creek Unit 1 prescribed fire (bottom).**

The actual Rough and Sheep Complex fires spanned multiple months. The Rough Fire had much larger downwind impacts which is related to the larger size of that fire in terms of acres burned and fuel consumed. The largest impacts from each of the fires is at the fire location itself with concentrations decreasing as distance from the fire increases. The episode average impacts for the hypothetical Boulder Creek Unit 1 prescribed fire are averaged over a much shorter time period (10 days) compared to the Rough and Sheep Complex fires which should be kept in consideration when comparing these spatial plots.

Each of the fires modeled as part of this case study have some impacts on populated areas in the Central Valley of California and further downwind toward the east. Some of the near-fire impacts on population areas may be overstated due to the 12-km-sized grid cells used for this case study, which may not capture complex terrain influenced meteorology and transport. This is particularly important to consider for the hypothetical Boulder Creek Unit 1 fire since the days for this fire were selected based on meteorology that was considered conducive to keeping air in the mountains and minimizing downslope flow to the Central Valley.

Each of the fires modeled in this case study produce fairly small levels of MDA8 $O_3$ compared with regional levels measured at surface monitor sites during the same time periods (Figure 5-14). The spatial nature of elevated MDA8 $O_3$ in California suggest sources other than wildland fire (e.g., anthropogenic, biogenic, lateral boundary inflow) contributed the most to ambient surface level $O_3$.

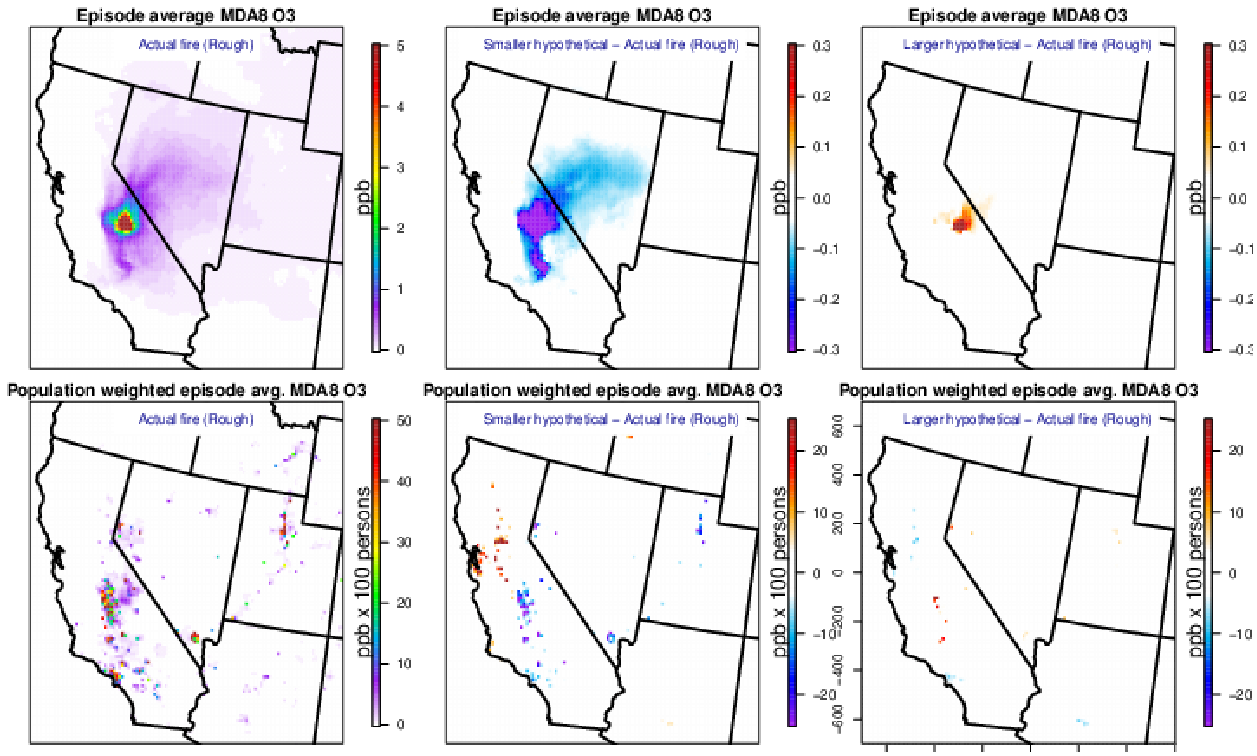
Episode average model predicted $PM_{2.5}$ from the actual Rough Fire is shown in Figure 5-15. Model predictions are also multiplied by gridded population to provide an estimate of aggregated population exposure. Figure 5-15 also shows the difference in episode average $PM_{2.5}$ between the hypothetical scenarios and actual fire scenario. Similar information is presented for MDA8 $O_3$ in Figure 5-16.




µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Note: Ambient $PM_{2.5}$ impacts are shown in the top row and aggregate population exposure in the bottom row where estimated $PM_{2.5}$ concentrations are multiplied by gridded population.

**Figure 5-15 Episode average $PM_{2.5}$ impacts from the actual Rough Fire and the difference between the actual scenario and smaller (Scenario 1) and larger (Scenario 2) hypothetical scenarios.**




avg = average; MDA8 = maximum daily 8-hour average; $O^3$ = ozone; ppb = parts per billion.

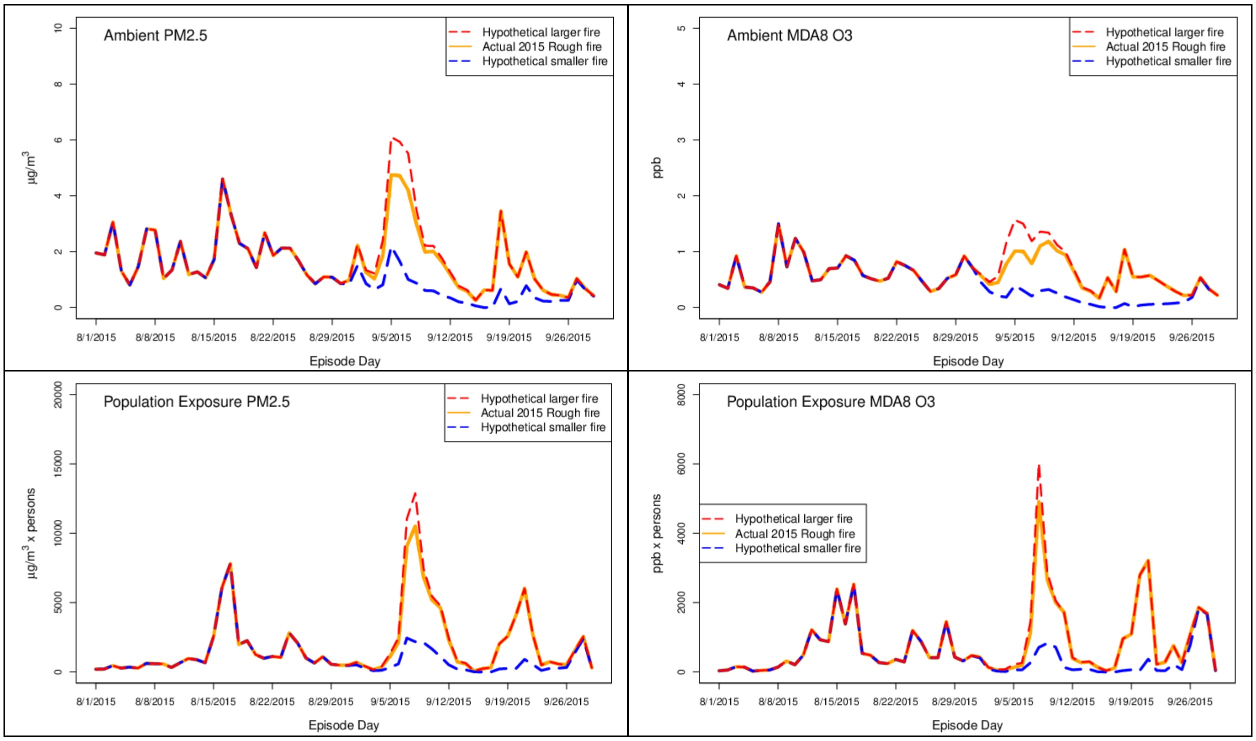
Note: MDA8 $O^3$ impacts are shown in the top row and aggregate population exposure in the bottom row where estimated MDA8 $O^3$ concentrations are multiplied by gridded population.

**Figure 5-16 Episode average maximum daily 8-hour average (MDA8) ozone ($O_3$) impacts from the actual Rough Fire and the difference between the actual scenario and smaller (Scenario 1) and larger (Scenario 2) hypothetical scenarios.**

The ambient impacts of the actual fires and hypothetical wildfire scenarios are highest in California and decrease downwind as air moves smoke into the intermountain west and central plains. When the impacts are multiplied by population most urban areas in the model domain have nonzero impacts. This shows that very small concentrations of smoke in large population areas can result in similar aggregated exposure to sparsely populated areas near the fire.

Rough Fire impacts on regional MDA8 $O_3$ are highest near the fire with smaller impacts in the Central Valley of California and central Nevada. Population impacts are also notable in large downwind urban areas like Salt Lake City. A very small opposite response in MDA8 $O_3$ is seen in the northern Central Valley of California for both alternative scenarios. This feature is magnified when applying population due to the very large number of people living in that part of the state. In this situation, changes in available oxidants and precursors has a small impact on model predicted $O_3$.

Figure 5-17 shows daily domain average $PM_{2.5}$ ambient impacts and aggregate population exposure from the actual and hypothetical Rough Fire scenarios. Similar information is shown for MDA8 $O_3$ in Figure 5-17.

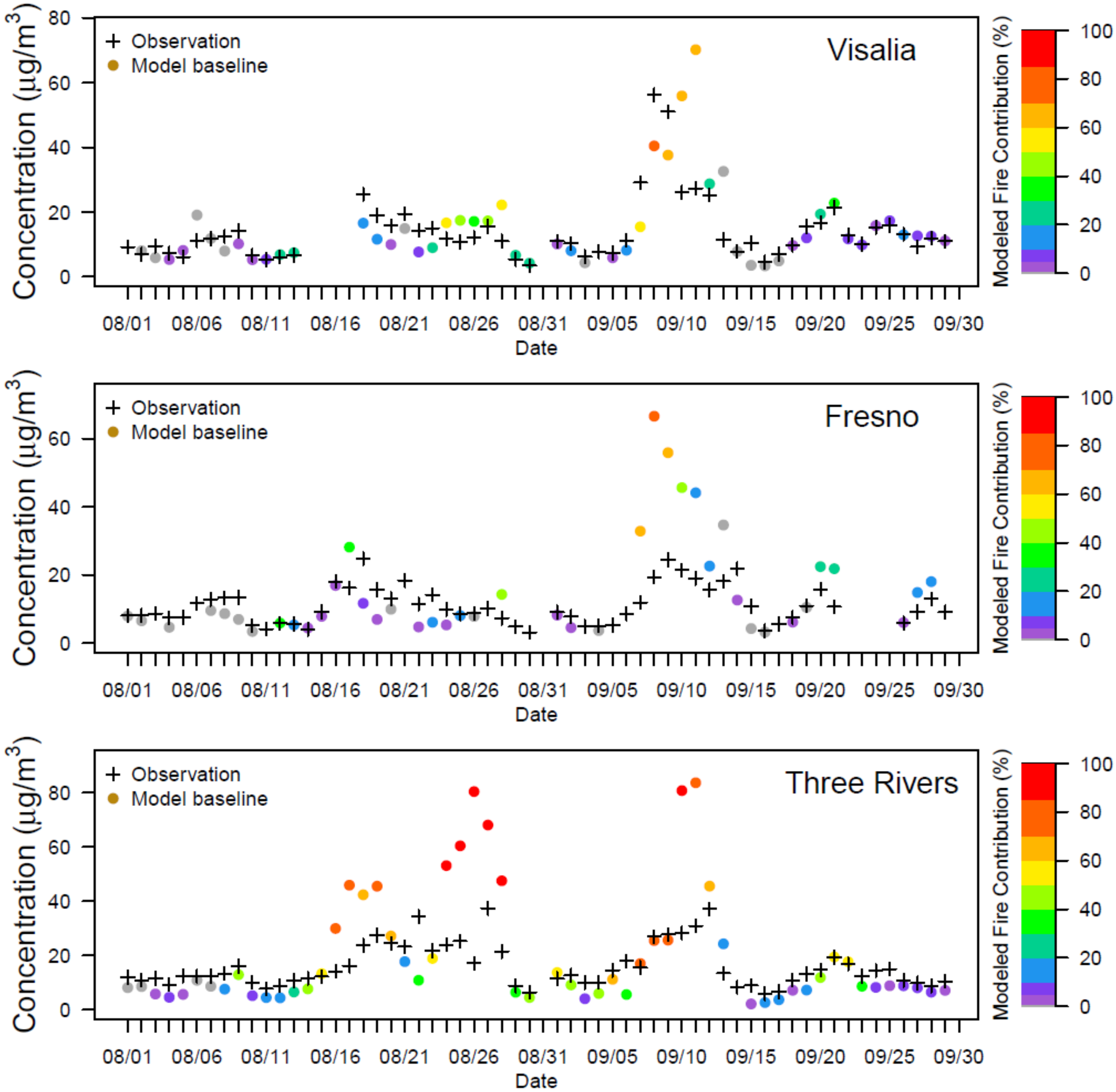



MDA8 = maximum daily 8-hour average; µg/m³ = micrograms per cubic meter; $O^3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; ppb = parts per billion.

**Figure 5-17 Daily average $PM_{2.5}$ ambient (left) and maximum daily 8-hour average (MDA8) ozone ($O_3$) (right) impacts and aggregate population exposure (bottom row) from the Rough Fire scenarios.**

Daily average impacts are the same for each scenario during the first month of the fire because the emissions are the same. The alternative scenarios diverge from the actual fire at the beginning of September. Aggregate population exposure is greatest when the model predicts impacts in the Central Valley of California for a period in early September and again to a lesser extent in mid-September. Ambient impacts are reduced in the smaller fire hypothetical scenario once the actual fire progresses to the Boulder Creek Unit 1 area and increases in the larger fire hypothetical scenario when the actual fire also includes the area of the Sheep Complex Fire.

Figure 5-18 shows daily $PM_{2.5}$ measurements and model predictions at multiple monitors in the Central Valley of California. These monitors were selected to provide an indication about how well the model captures smoke impacts from the Rough Fire. The model tends to overpredict $PM_{2.5}$ impacts at these monitors when a large contribution from the Rough Fire is predicted. However, there were days at Visalia when the model underpredicted $PM_{2.5}$ impacts toward the beginning of early September. These overpredictions may be related to $PM_{2.5}$ emissions, physical treatment of the plume (evaporation and condensation processes), transport, grid resolution, or some combination of these factors. The large estimated population exposures of the Rough Fire are most likely overstated during the early September period of high modeled fire impacts in the Central Valley of California. Some of the model overprediction at monitors that were impacted by smoke may be related to the model treating primarily emitted organic aerosol as nonvolatile. If some amount of the primarily emitted organic aerosol was allowed to evaporate in the model, then downwind surface concentrations would be smaller. This treatment would result in model predictions closer to measurements as fire impact monitors were often over-predicted (Figure 5-18).

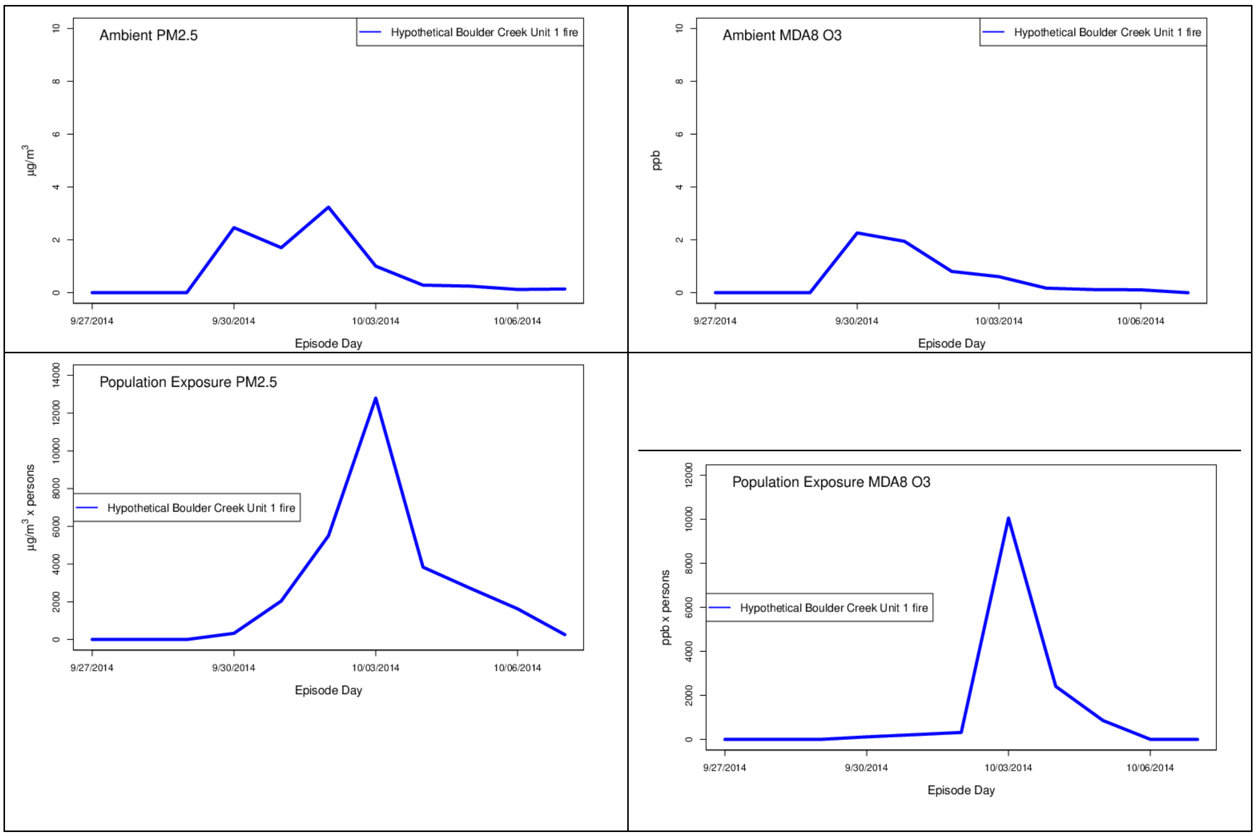



µg/m³ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Note: Model predictions are shaded by the percent contribution from the actual Rough Fire.

**Figure 5-18 Daily average $PM_{2.5}$ observations and model predictions at monitors in the Central Valley of California for August and September 2015.**

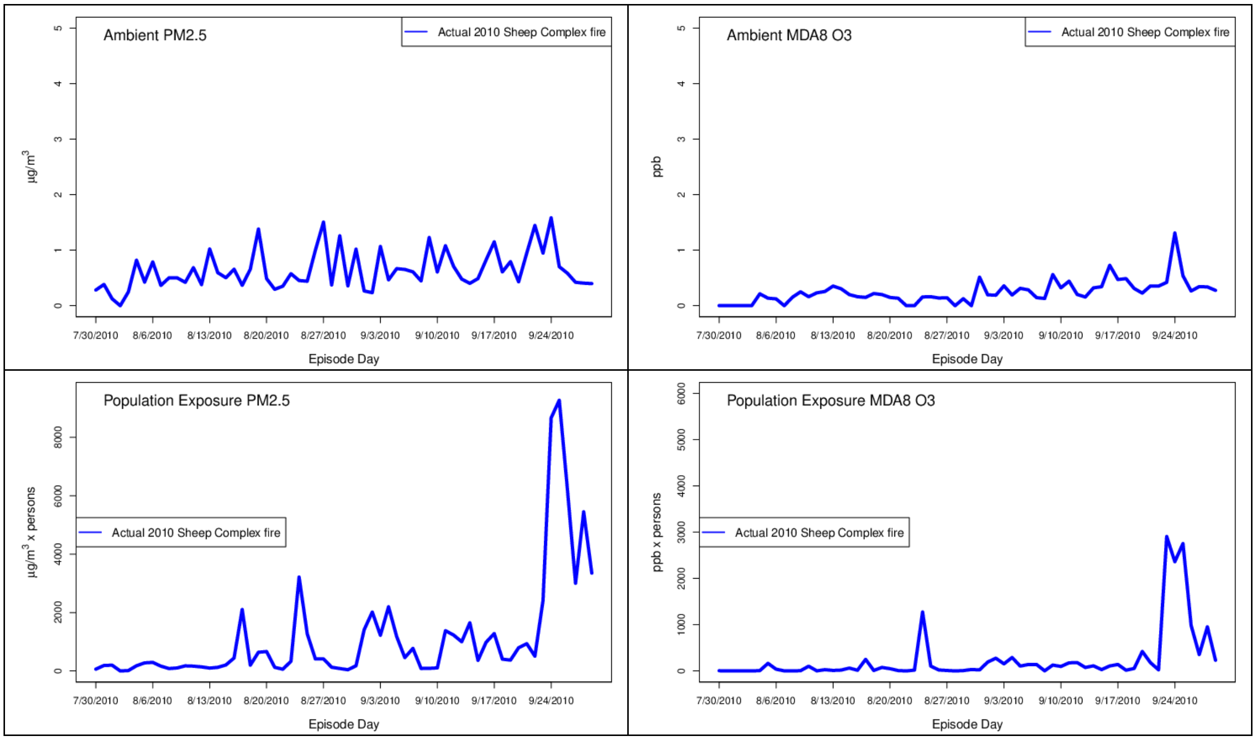
Ambient impacts of the hypothetical Boulder Creek Unit 1 prescribed fire (Figure 5-19) are notably smaller on the last 2 days than the first 3 days. Aggregate population exposures are high on 1 day toward the end of the prescribed fire when winds blew smoke toward the Central Valley of California. It is possible that the grid resolution used in this study may exaggerate estimates of population exposure as terrain-influenced meteorology may be not well resolved with 12-km-sized grid cells for this particular fire. The 12-km-sized grid cell resolution was chosen for the Rough Fire related scenarios to capture potential continental scale impacts at the expense of capturing near-fire orographic effects. While daily air quality impacts from the Boulder Creek Unit 1 prescribed fire are similar in magnitude with some days of the Rough Fire, the estimates of population exposure are much smaller due to the meteorology on those days not transporting smoke to large population areas in central California and isolated to a much smaller number of days.




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $O_3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

**Figure 5-19 Daily average $PM_{2.5}$ ambient (left) and maximum daily 8-hour average (MDA8) ozone ($O_3$) (right) impacts and aggregate population exposure (bottom row) from the hypothetical Boulder Creek Unit 1 prescribed fire.**

Daily air quality impacts of the actual Sheep Complex Fire in 2010 (Figure 5-20) are fairly steady with respect to ambient concentrations and aggregate population exposure. A short period of high PM and $O_3$ impacts in populated areas was evident at the end of the fire in late September when the model predicted winds transporting smoke to more populated areas of the Central Valley in California. The daily ambient concentrations of the Sheep Complex Fire tend to be lower than the Rough Fire and aggregate population exposures are much lower than the Rough Fire. This is attributed to the smaller amount of biomass burned on a given day during the Sheep Complex Fire compared with the Rough Fire.




MDA8 = maximum daily 8-hour average; μg/m$^3$ = micrograms per cubic meter; $O_3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; ppb = parts per billion.

**Figure 5-20 Daily average ambient $PM_{2.5}$ (left) and maximum daily 8-hour average (MDA8) ozone ($O_3$) (right) concentrations and estimates of aggregate population exposure (bottom row) from the 2010 Sheep Complex Fire.**

## 5.4 Limitations, Implications, and Recommendations

Since the air quality impacts of these wildfire and prescribed fire scenarios occur over different time scales the aggregation of impacts is presented later in this report in the section covering human health effects (see CHAPTER 8) with a synthesis of the results of the air quality modeling and health impact analyses in CHAPTER 9. A summary of highlights from the air quality modeling of the case study fires follows.

- Surface fuel load characterization is an important component of modeling air quality impacts associated with wildfires and prescribed fires.
- Outputs from two established fuel load characterization models, FCCS and VELMA, were merged and fed into the BlueSky Pipeline to simulate air quality impacts associated with wildfire and prescribed fire simulations for the TC6 and Rough Fire case studies.
- Whereas FCCS excels at providing estimates of management-sensitive surface and understory fuel types and loads, VELMA excels at characterizing overstory/canopy fuel loads through its use of linked forest inventory and satellite-based (LEMMA) data. The combined use of FCCS and VELMA for this purpose plays to the strengths of both models to better characterize fine-scale horizontal and vertical distributions of fuelbed types and loadings.
- Applied photochemical grid model to estimate $PM_{2.5}$ and $O_3$ impacts from an actual wildfire in Oregon and California
- Photochemical model was also used to estimate how $PM_{2.5}$ and $O_3$ impacts change for hypothetical smaller and larger realizations of the actual fires

In considering the assumptions and approach used in the air quality modeling for the case studies presented in this report, it is important to consider the limitations of these analyses to ensure the results are interpreted in the proper context. The prescribed fire impacts presented here represent a small subset of meteorological conditions, fuel loadings, and timing choices and may not be reflective of potential impacts on air quality in other areas or under different conditions.

For example, despite widespread prescribed fire activity in the southeastern U.S., there are currently no areas in the Southeast that are noncompliant with the PM or $O_3$ National Ambient Air Quality Standard. This widespread regional compliance with existing NAAQS across the Southeast suggests that carefully chosen timing of prescribed fire coupled with anthropogenic control programs can provide an opportunity for meeting land management goals without compromising public health. However, when prescribed burning activity is concentrated into a small window of time, which is typical for example in the Flint Hills region of central Kansas, the enormous amount of fuel being burned on a few days has led to downwind monitors with $O_3$ and $PM_{2.5}$ sometimes exceeding the level of the NAAQS (Baker et al., 2019).

One challenge related to scale is understanding how the case study information provided in this report would translate to larger fires (size, duration) or larger regions where many fires would be on the landscape. The case studies within this assessment are somewhat limited in considering trade-offs over time because land management techniques would be conducted over multiple years to meet historical fire return interval goals while these case studies are episodic. Further, information about how many acres/total fuel needs to be burned in addition to the time interval between burns is needed to place the information here into a broader context of land management and air quality impacts.

Future studies should attempt to include emissions related to fire suppression activity and model near-fire impacts using a horizontal grid resolution that would best capture complex terrain impacts on wind patterns.

While the interactions between prescribed burns and wildfire characteristics is an active area of research (Hunter and Robles, 2020), more information is needed to understand and apply these dynamics quantitatively in air quality models, especially at the regional and national scales. The lack of a generalizable, mechanistic understanding of the influence of prescribed burning and other land treatments on wildfire activity (and consequently on air pollution due to wildfires) remains a major source of uncertainty when projecting future changes in fire-related air quality impacts, especially in areas where prescribed burning is a common practice.

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# CHAPTER 6 WILDLAND FIRE SMOKE EXPOSURE CHARACTERIZATION AND HEALTH AND ECOLOGICAL IMPACTS

## 6.1 Introduction

Wildland fire (i.e., prescribed fire and wildfire) smoke can have detrimental effects on both human and ecological health, but can also provide ecological benefits (see Section 6.4.1.2) as well as cultural benefits when used as part of indigenous cultural fires (Raish et al., 2005). While the health impacts of wildfire smoke exposure can be quantitatively estimated using the Environmental Benefits Mapping and Analysis Program—Community Edition [BenMAP-CE;U.S. EPA (2019a)], it is much more challenging to quantify the potential ecological impacts. This chapter summarizes the health effects attributed to wildfire smoke exposure, with a focus on U.S.-based epidemiologic studies; characterizes the different actions and interventions that can be employed at a population and individual level to reduce smoke exposure; and highlights the ecological impacts attributed to wildfire smoke. The evaluation of epidemiologic studies is meant to inform the estimation of potential health impacts of smoke from wildfires based on different fire management strategies, including prescribed fire, within the case study areas using BenMAP-CE (see CHAPTER 8).

In assessing the evidence base spanning both human and ecological health, the current understanding of impacts from wildland fire smoke primarily stems from studies examining effects due to exposures to ambient fine particulate matter ($PM_{2.5}$; particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm ), with a growing body of evidence focusing specifically on wildfire smoke, and only a few studies focusing on prescribed fires. While smoke also contains precursors that can lead to ozone formation downwind from a wildland fire (see CHAPTER 5), fewer studies have examined wildfire-specific health impacts attributed to ozone. However, extensive evidence demonstrating health effects from ambient ozone exposures indicates the potential for ozone formed from wildfires to result in an additional significant public health burden (U.S. EPA, 2020a).

The extent of prescribed fire and wildfire smoke exposure depends on proximity to the fire and the location (i.e., not everyone is exposed to smoke from fires), duration, and intensity of smoke plumes. Therefore, it is plausible that individuals can take actions to reduce or mitigate exposure to smoke from prescribed fires or wildfires. In addition to identifying the potential human health impacts of smoke exposure, this chapter also evaluates and characterizes the effectiveness of various actions that can be taken to reduce smoke exposure and subsequently protect public health.

## 6.2 Wildfire Smoke Exposure and Health

Scientific evidence examining the health effects attributed to wildfire smoke exposure has grown significantly in recent years. The underpinnings of this evidence are rooted in the decades of research examining the health effects of ambient air pollutants, many of which are components of wildfire smoke. Of these components, particulate matter, specifically $PM_{2.5,}$ is a main component and has been shown to have a significant public health impact, which is demonstrated by the range of health effects attributed to $PM_{2.5}$ exposure, including respiratory and cardiovascular effects, as well as mortality (Jaffe et al., 2020; U.S. EPA, 2019b). Recent epidemiologic and experimental studies examining the health effects of wildfire smoke exposure report findings that are generally consistent with the broad body of evidence from studies examining short-term $PM_{2.5}$ exposure (U.S. EPA, 2019c; Black et al., 2017; Reid et al., 2016). The consistency in results across studies of wildfire smoke exposure and $PM_{2.5}$ are further supported by studies that compared the health effects associations between various sources of $PM_{2.5}$, including wildfire smoke, and ambient $PM_{2.5}$. These studies have not provided evidence indicating differences in the risk of health effects between different sources of $PM_{2.5}$ and total ambient $PM_{2.5}$ (DeFlorio-Barker et al., 2019; U.S. EPA, 2019b). However, it is important to note that experimental studies have provided evidence of differential toxicity and mutagenicity due to both the flaming and smoldering of different individual fuel sources, which may be important to consider when examining the trade-offs between prescribed fire and wildfire (Kim et al., 2018).

Most studies that examine the health effects of wildfire smoke exposure at the population level focus broadly on wildfire smoke, without accounting for potential differences in smoke emissions between prescribed fire and wildland fire. A recent epidemiologic study conducted by Prunicki et al. (2019) reported initial evidence of differences in markers of immune function, DNA methylation, and worsened respiratory outcomes in school-aged children in Fresno, CA exposed to wildfire smoke compared to prescribed fire smoke. The difference in effects observed coincided with lower concentrations of air pollutants from prescribed fires compared to wildfires. However, it is unclear what aspects of the difference between prescribed fires and wildfires resulted in the differential health effects (e.g., differences in duration, air pollutant concentrations, fuel types, burn conditions). Although Prunicki et al. (2019) provides initial evidence of potential differences in subclinical effects due to prescribed fire versus wildfire smoke exposure, it remains unclear if there are differences in more overt health effects (e.g., hospital admissions, mortality) between the two fire types.

Overall, wildfire smoke exposure studies report results that are generally consistent with epidemiologic studies of short-term $PM_{2.5}$ exposure, and are also remarkably consistent with each other considering the large degree of variability in both the exposure indicators (e.g., $PM_{2.5}$, wildfire-specific $PM_{2.5}$, smoke day) and exposure assessment methodologies employed. This variability across smoke indicator metrics directly influences the utility of results in quantitative assessments, such as a risk assessment or a cost-benefit analysis. Furthermore, as noted previously, there is limited evidence regarding the health effects attributed to ozone derived from wildland fire smoke even though there is extensive evidence of numerous health effects from studies of ambient ozone exposure (U.S. EPA, 2020a). As a result, this section consists of an evaluation of epidemiologic studies conducted within the U.S., published through December 2020, that could be used, either alone or in combination with studies of ambient $PM_{2.5}$ and ozone, in a quantitative assessment of the potential health impacts associated with different fire management strategies in the case study areas (i.e., Timber Crater 6 [TC6] Fire and Rough Fire), identified in earlier chapters, using U.S. EPA's Environmental BenMAP-CE, (see CHAPTER 7). Based on the majority of the wildfire smoke epidemiologic studies focusing on $PM_{2.5}$ and because of the consistency in health effects between studies of short-term $PM_{2.5}$ and wildfire smoke exposure the epidemiologic studies evaluated within this section consist of those that examined health outcomes where the most recent U.S. EPA Integrated Science Assessment for Particulate Matter concluded that the evidence indicates either a "causal relationship" or "likely to be causal relationship" (i.e., respiratory and cardiovascular effects, and mortality). This approach is in line with the criteria used by the U.S. EPA in the process of conducting BenMAP-CE analyses.

This assessment of the health effects of wildfire smoke exposure is not intended to be an exhaustive review of the evidence. Recent reviews and interagency efforts have extensively characterized the current state of the science with respect to the health effects attributed to wildfire smoke exposure (Jaffe et al., 2020; U.S. EPA, 2019c; Reid et al., 2016). In addition, it is important to recognize that the evaluation with this assessment does not rely on the numerous animal toxicological studies conducted to date that focused on examining health effects from exposures consisting of wildfire smoke from fuel sources commonly found in the U.S. (e.g., individual tree species) or real-world wildfire smoke.

### 6.2.1 Characterization of Wildfire Smoke Exposures

Wildfires are often natural, spontaneous events, which has complicated the ability of epidemiologic studies to characterize population exposures to wildfire smoke. As a result, studies have used a variety of approaches to estimate wildfire smoke exposure in terms of both the exposure indicator and exposure assessment methodology used (Table A.6-1). While the exposure assessment approaches used across studies vary in complexity and in the specificity of the indicator in representing wildfire smoke exposure, epidemiologic studies report generally consistent associations between short-term wildfire smoke exposure and health effects (Section 6.2.2).

#### 6.2.1.1 Exposure Indicator

Within epidemiologic studies, the exposure indicator is a quantity meant to represent exposure to an environmental contaminant. For wildfire smoke, which consists of a complex mixture of pollutants, various indicators have been used as a surrogate for wildfire smoke exposure. These indicators vary in specificity and sensitivity with respect to how well they represent exposure to wildfire smoke. Because of the public health implications of exposure to $PM_{2.5}$ and $PM_{2.5}$ being a main component of wildfire smoke, studies often rely on the use of some form of $PM_{2.5}$ as an exposure indicator. Some epidemiologic studies used monitored or modeled $PM_{2.5}$ concentrations as the exposure indicator (Alman et al., 2016; Reid et al., 2016; Delfino et al., 2009) while other studies used wildfire or smoke-specific $PM_{2.5}$, which consisted of removing $PM_{2.5}$ derived from other $PM_{2.5}$ sources from the concentrations estimated (Stowell et al., 2019; Gan et al., 2017; Rappold et al., 2012). Additionally, some studies use $PM_{2.5}$ concentrations or estimate a range of $PM_{2.5}$ concentrations from an atmospheric model to develop an exposure indicator based on classifying days as either smoke or nonsmoke days or by assigning each day a level of smoke density (i.e., light, medium, or dense). In these studies the defining of days by smoke status often depended on using criteria to define specific ranges of $PM_{2.5}$ concentrations that are considered indicative of wildfire smoke exposure (Jones et al., 2020; Wettstein et al., 2018; Liu et al., 2017b; Liu et al., 2017a). The use of a broad exposure indicator, such as smoke days, may be more representative of the multipollutant nature of wildfire smoke. However, to date there has been no indication that any one exposure indicator represents a better surrogate of wildfire smoke exposure than another. Overall, the variability in the exposure indicator used across studies partly reflects the difficulty in examining the health effects of wildfire smoke exposure, and the air quality data available, or lack thereof in some instances (see CHAPTER 4).

#### 6.2.1.2 Exposure Assessment Methodology

Estimating wildfire smoke exposure for epidemiologic studies is challenging because wildfire smoke is spatially and temporally dynamic and areas impacted by wildfire smoke often have few ambient monitoring sites because most air quality monitors reside in urban locations (see CHAPTER 4). As a result, epidemiologic studies have resorted to using numerous methods that vary in complexity to assign exposures (Table A.6-1). In contrast, due to the planned nature of prescribed fires, monitors could be deployed to capture population exposure, but to date have not been widely used in this capacity and the data is not always reported (see CHAPTER 4).

Consistent with many epidemiologic studies of ambient air pollution, a few studies examined relationships between short-term wildfire smoke exposure and health effects using monitored $PM_{2.5}$ concentrations and some approach to assign exposures to a defined spatial extent, whether that be a city or ZIP code (Leibel et al., 2020; Zu et al., 2016). Most epidemiologic studies focusing on wildfire smoke exposure use exposure models that rely on data from multiple sources and are often referred to as hybrid exposure models. These models use both monitoring and modeling data, and in some instances satellite measurements to take advantage of all the data available to estimate wildfire or smoke-specific $PM_{2.5}$ concentrations. Incorporating all these data sources into the model allows for a broader spatial extent to be included in epidemiologic studies instead of being limited to only those locations within reasonable proximity to air quality monitors, which are primarily in urban centers. Relatively few of the studies that used hybrid exposure models evaluated model performance, but those studies that did indicate the models performed rather well [see Table A.6-1; Reid et al. (2019); Stowell et al. (2019); Gan et al. (2017); Reid et al. (2016).

A few epidemiologic studies relied on other approaches to estimating wildfire smoke exposure. While often included as a component in the exposure model to estimate wildfire smoke, one study used only satellite measurements (i.e., aerosol optical depth [AOD]) to identify areas that were impacted by a smoke plume (Rappold et al., 2011). The remaining studies used various models that were developed to examine wildfire smoke exposures by estimating either wildfire-specific $PM_{2.5}$ exposure or smoke exposure more broadly. Studies that estimated wildfire-specific $PM_{2.5}$ exposure used the Wildland Fire Emissions Information System (WFEIS) or National Oceanic and Atmospheric Administration's (NOAA's) Smoke Forecasting System (SFS) in combination with the transport and dispersion model HYSPLIT (Hutchinson et al., 2018; Tinling et al., 2016; Rappold et al., 2012) while studies that focused on smoke days used NOAA's Hazard Mapping System (HMS) to characterize exposure based on the density of smoke (Jones et al., 2020; Wettstein et al., 2018).

Regardless of the exposure assessment approach used, the results across epidemiologic studies provide evidence supporting a relationship between wildfire smoke exposure and various health effects (see Section 6.2.2). However, the variability in the exposure approaches used does not allow for the results from some epidemiologic studies, such as those that used indicator variables to represent wildfire smoke, to be used for the development of wildfire-specific health impact functions in BenMAP-CE analyses.

#### 6.2.1.3 Uncertainties and Limitations in Characterizing Wildfire Smoke Exposure

A challenge in estimating wildland fire smoke exposure, as detailed within CHAPTER 4, is the fact the current ambient monitoring network was not designed with the goal of measuring smoke from wildfires or public health surveillance. As a result, as noted within this section, epidemiologic studies have relied on a variety of approaches to estimate smoke exposure, whether through $PM_{2.5}$ concentration data collected from the ambient monitoring network, predicted concentrations from photochemical transport models, satellite measurements or a combination each, as well as estimations of smoke plumes. Although results across epidemiologic studies are consistent regardless of the approach used to assign exposure (see Section 6.2.2), there are inherent uncertainties across each of the approaches employed, with one of the larger uncertainties being how well exposures represented by smoke plumes reflect $PM_{2.5}$ concentrations experienced on the ground. However, a recent study by Larsen et al. (2018) that examined $PM_{2.5}$ monitoring and smoke plume data and found initial evidence that monitored values on the ground reflect the presence of smoke plumes in the vertical column measured by satellites. In the future, more detailed evaluations of the different approaches that can be used and a characterization of their strengths and weaknesses will aid in further supporting the interpretation of results from epidemiologic studies.

### 6.2.2 Health Effects Attributed to Wildfire Smoke Exposure

In the context of wildfires, most U.S.-based studies focus on short-term or daily exposures (i.e., 24-hour average). Across these studies, the primary pollutant of interest is $PM_{2.5}$, with only one study focusing on ozone (Reid et al., 2019). Studies examining exposure durations shorter than a 24-hour average, often referred to as subdaily exposures, have been limited to epidemiologic and controlled human exposure studies of ambient $PM_{2.5}$ focusing on subclinical measures of heart or lung function and not overt population-level effects, such as hospital admissions or mortality (U.S. EPA, 2019b). Therefore, these studies of subdaily exposures do not directly inform the relationship between shorter duration wildfire smoke exposures and health effects due to the difficulty in linking a change in a subclinical effect to an overt health outcome. As a result, most of the evidence informing the current understanding of health effects attributed to wildfire smoke exposure stems from epidemiologic studies primarily focusing on examining exposures over single-day or multiday lags ranging from 0 to 5 days.

The focus on examining health effects attributed to short-term wildfire smoke exposures has resulted in a relative lack of information on the health effects due to repeated wildfire smoke exposures (i.e., over many days, weeks, or months); the long-term health effects of wildfire smoke exposure from a single wildfire event; and the health effects due to long-term wildfire exposures over many months and multiple fire seasons. To date, studies have not examined the impact of repeated wildfire smoke exposure on health; whereas, an initial study provides preliminary evidence that a wildfire smoke event with high $PM_{2.5}$ concentrations may detrimentally impact health, specifically lung function, over multiple subsequent years (Orr et al., 2020). The examination of longer-term exposures to wildfire smoke has been limited to a recent study indicating increased risk of mortality in hemodialysis patients as cumulative exposures increase up to 30 days (Xi et al., 2020), analyses of subclinical effects (e.g., changes in lung function) in wildland fire fighters over multiple fire seasons (Adetona et al., 2016), and a study examining the potential implications of wildfire smoke exposure on the influenza season (Landguth et al., 2020).

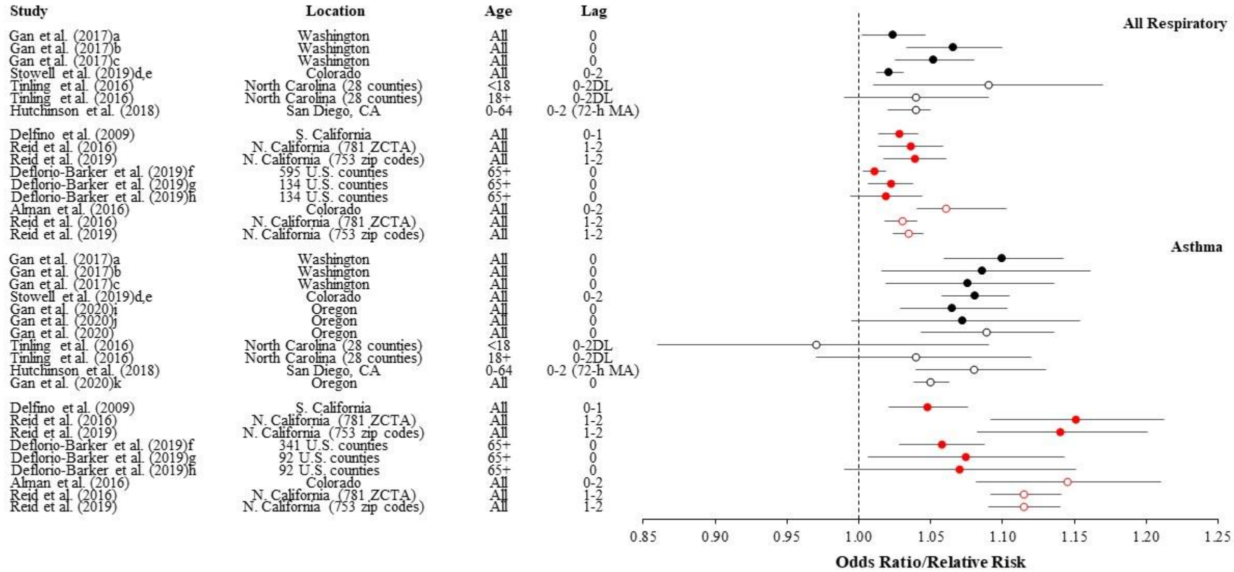
#### 6.2.2.1 Respiratory Effects

Most studies to date specifically examining the health effects of wildfire smoke exposure focus on respiratory-related outcomes (e.g., emergency department [ED] visits, hospital admissions, and medication use). In addition to the wildfire-specific evidence, there is extensive evidence spanning both experimental and epidemiologic studies focusing on short-term exposures to ambient $PM_{2.5}$ demonstrating a range of respiratory effects, with the strongest evidence supporting relationships with exacerbations of asthma and chronic obstructive pulmonary disease (COPD), as well as respiratory mortality (U.S. EPA, 2019b).

Epidemiologic studies that examined relationships between short-term wildfire smoke exposure and respiratory-related outcomes also provide evidence of positive associations, which are consistent with the results of studies focusing on ambient $PM_{2.5}$. The pattern of associations across studies of wildfire smoke and ambient $PM_{2.5}$ are generally observed within the first few days after exposure [i.e., at lags in the range of 0−2 days; U.S. EPA (2019b); Figure 7-1 and Figure 7-2]. However, there has been limited examination of longer durations of exposure (i.e., exposures over multiple days) for both ambient $PM_{2.5}$ and wildfire exposures and respiratory effects. Initial evidence indicates respiratory effects of larger magnitude due to prolonged exposure (i.e., over a series of days with lags ranging from 0 to 5 days), which is important to consider when examining wildfire smoke exposure that often lasts for many weeks or months (U.S. EPA, 2019b; Rappold et al., 2011).

Across the epidemiologic studies examining respiratory-related outcomes, the most extensive evidence comes from studies examining combinations of respiratory-related diseases (i.e., all International Classification of Diseases [ICD] codes for the entire range of respiratory diseases or a subset of ICD codes for only a few respiratory diseases, noted as “all respiratory” in Figure 6-1) and asthma. These studies provide consistent evidence of positive associations for both ED visits and hospital admissions when using different exposure indicators, including smoke/wildfire $PM_{2.5}$ or ambient $PM_{2.5}$ (Figure 6-1). Some of the studies evaluated examined whether there was evidence of differential risk across age groups (Table A.6-1), and while in some instances the magnitude of the association was reported to be larger for a specific age range, the results presented in Figure 6-1, capture the main results of each study.

In addition to the studies that relied on $PM_{2.5}$ to develop the exposure indicator, studies that used alternative exposure indicators or applied different techniques to identify wildfire smoke exposures provide supporting evidence of a relationship between short-term wildfire smoke exposure and respiratory effects. Studies that used the exposure indicator of smoke plume or smoke density reported evidence of consistent positive associations when examining both combinations of respiratory-related diseases and asthma (Wettstein et al., 2018; Rappold et al., 2011). Instead of examining associations with respiratory outcomes, Leibel et al. (2020) in a study conducted in San Diego County, CA examined, and subsequently reported, evidence of excess ED visits and urgent care visits for combinations of respiratory-related diseases during wildfire periods compared to a control period. Lastly, Liu et al. (2017a) reported a positive association between wildfire $PM_{2.5}$ and respiratory disease hospital admissions when 2 consecutive days of wildfire $PM_{2.5}$ concentrations (i.e., a smoke wave) were greater than 37 $\mu g/m^3$.




DL = distributed lag; CMAQ = Community Multiscale Air Quality; ED = emergency department; GWR = geographically weighted ridge regression; MA = moving average; µg/m³ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; WRF = Weather Research and Forecasting; ZCTA = ZIP-code tabulation area.

Black circles = studies that used smoke/wildfire $PM_{2.5}$ as the exposure indicator; red circles = studies that used ambient $PM_{2.5}$ measurements as the exposure indicator; solid circles = hospital admissions; open circles = ED visits; odds ratios and relative risks, unless otherwise noted, are for a 10 µg/m³ increase in smoke/wildfire or ambient $PM_{2.5}$ concentrations.

[a]exposure estimated using WRF-Chem smoke.

[b]exposure estimated from kriging.

[c]exposure estimated using GWR smoke $PM_{2.5}$.

[d]Estimate is for a 1 µg/m³ increase in wildfire $PM_{2.5}$.

[e]Combination of Hospital Admissions and ED Visits.

[f]$PM_{2.5}$ Tot-CMAQ with indicator variable for smoke day.

[g]$PM_{2.5}$ Tot-CMAQ-Monitor with indicator variable for smoke day.

[h]$PM_{2.5}$ from monitors with indicator variable for smoke day.

[i]Outpatient hospital admission.

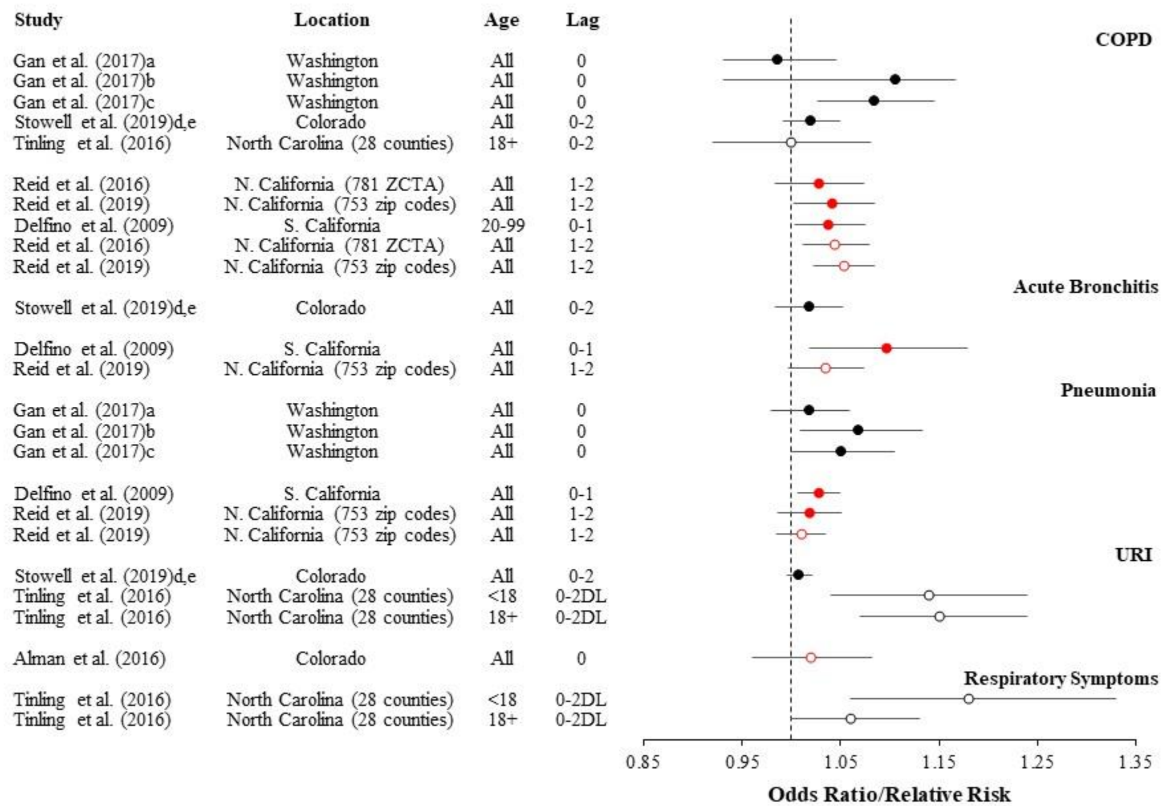
[j]Inpatient hospital admission.

[k]Office visit.

**Figure 6-1 Odds ratios and relative risks from U.S.-based epidemiologic studies examining the relationship between short-term wildfire smoke exposure and combinations of respiratory-related diseases and asthma emergency department visits and hospital admissions.**

Several epidemiologic studies also examined associations between short-term wildfire smoke exposure and other respiratory diseases, including COPD, acute bronchitis, pneumonia, upper respiratory infections (URIs), and respiratory symptoms. Consistent with the studies that examined all respiratory diseases and asthma ED visits and hospital admissions, these studies indicate an increased risk following exposure for a range of respiratory effects (Figure 6-2). Examples include Rappold et al. (2011), which reported positive associations for COPD, pneumonia and acute bronchitis, and URI in North Carolina counties exposed to wildfire smoke estimated by using smoke plume data, as well as Liu et al. (2017b) which reported positive associations for hospital admissions related to COPD and respiratory infection in adults 65 years of age an older exposed to two or more consecutive days to wildfire $PM_{2.5}$ concentrations >37 μg/m$^3$.

While the most extensive examination of the health effects attributed to wildfire smoke exposure is based on exposure indicators that rely on $PM_{2.5}$, populations can experience exposure to additional pollutants, such as ozone as a result of the mixture of pollutants emitted from wildfires undergoing atmospheric reactions in the presence of sunlight (U.S. EPA, 2019c). There is extensive evidence indicating a relationship between short-term ozone exposure and respiratory effects including changes in lung function and asthma-related ED visits and hospital admissions (U.S. EPA, 2020a). A recent study by Reid et al. (2019) examined the relationship between ozone produced from wildfire events and respiratory health. The authors reported the strongest evidence of an association with asthma and combinations of respiratory-related ED visits during the fire, but the results across all of the respiratory outcomes examined were attenuated in copollutant models with $PM_{2.5}$ even though the correlation between ozone and $PM_{2.5}$ was low ($r$ = 0.195), indicating the complexity in examining health effects attributed to both primary pollutants and secondary pollutants from wildfire smoke.




COPD = chronic obstructive pulmonary disease; DL = distributed lag; ED = emergency department; µg/m$^3$ = micrograms per cubic meter; GWR = geographically weighted ridge regression; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; URI = upper respiratory infection; WRF = Weather Research and Forecasting; ZCTA = ZIP-code tabulation area.

Black circles = studies that used smoke/wildfire $PM_{2.5}$ as the exposure indicator; red circles = studies that used ambient $PM_{2.5}$ measurements as the exposure indicator; solid circles = hospital admissions; open circles = ED visits; odds ratios and relative risks, unless otherwise noted, are for a 10 µg/m$^3$ increase in smoke/wildfire or ambient $PM_{2.5}$ concentrations.

[a]exposure estimated using WRF-Chem smoke.

[b]exposure estimated from kriging.

[c]exposure estimated using GWR smoke $PM_{2.5}$.

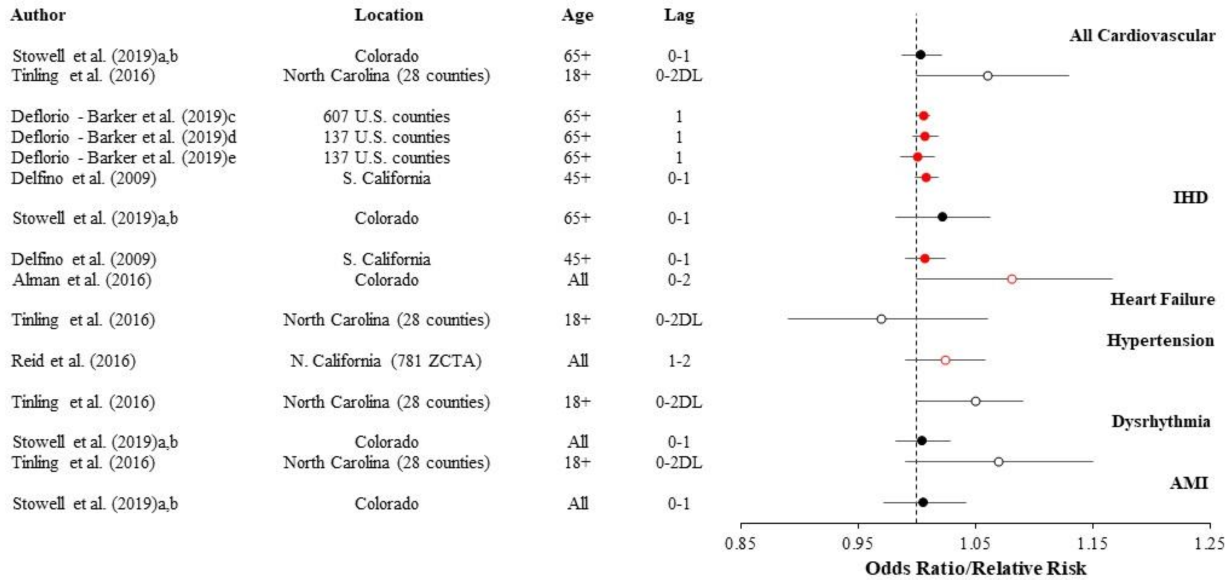
[d]Estimate is for a 1 µg/m$^3$ increase in wildfire $PM_{2.5}$.

[e]Combination of hospital admissions and ED visits.

**Figure 6-2 Odds ratios and relative risks from U.S.-based epidemiologic studies examining the relationship between short-term wildfire smoke exposure and respiratory-related emergency department visits and hospital admissions.**

#### 6.2.2.2 Cardiovascular Effects

There is extensive experimental and epidemiologic evidence indicating a relationship between short-term $PM_{2.5}$ exposure and cardiovascular effects, particularly for ischemic heart disease (IHD) and heart failure (HF) as well as cardiovascular mortality (U.S. EPA, 2019b). While there is a more limited evidence base related to the effects of wildfire smoke exposure on cardiovascular health, compared to respiratory outcomes, these studies report generally positive associations albeit with wide confidence intervals (Figure 6-3), with the magnitude of associations being relatively consistent to those reported in studies of ambient $PM_{2.5}$ (U.S. EPA, 2019b).




AMI = acute myocardial infarction; DL = distributed lag; ED = emergency department; µg/m$^3$ = micrograms per cubic meter; GWR = geographicaly weighted ridge regression; IHD = ischemic heart disease; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; WRF = Weather Research and Forecasting; ZCTA = ZIP-code tabulation area.

Black circles = studies that used smoke/wildfire $PM_{2.5}$ as the exposure indicator; red circles = studies that used ambient $PM_{2.5}$ measurements as the exposure indicator; solid circles = hospital admissions; open circles = ED visits; odds ratios and relative risks, unless otherwise noted, are for a 10 µg/m$^3$ increase in smoke/wildfire or ambient $PM_{2.5}$ concentrations.

[a]Estimate is for a 1 µg/m$^3$ increase in wildfire $PM_{2.5}$.

[b]Combination of hospital admissions and ED visits.

[c]exposure estimated using WRF-Chem smoke.

[d]exposure estimated from kriging.

[e]exposure estimated using GWR smoke.

**Figure 6-3 Odds ratios and relative risks from U.S.-based Epidemiologic studies examining the relationship between short-term wildfire smoke exposure and cardiovascular-related emergency department (ED) visits and hospital admissions.**

Several studies examining cardiovascular effects used indicators of smoke events to capture the spatial and temporal extent of exposure (Wettstein et al., 2018; Liu et al., 2017a; Rappold et al., 2011). In a study of 561 western U.S. counties, Liu et al. (2017a) did not report any evidence of an association between total cardiovascular-related hospital admissions and smoke wave days (i.e., two consecutive days with wildfire $PM_{2.5}$ concentrations >20 µg/m$^3$) in adults 65 years of age and older. However, in a study of ED visits within 42 North Carolina counties, Rappold et al. (2011) reported an increased risk for combined cardiovascular-related outcomes. When examining, cause-specific cardiovascular outcomes, the authors reported the strongest evidence of an association for heart failure and myocardial infarction. Similarly, in a study of eight California air basins Wettstein et al. (2018) reported an increased risk of ED visits across combined cardiovascular outcomes at medium ($PM_{2.5}$ concentrations between 10−19 µg/$m^3$) and dense ($PM_{2.5}$ concentrations >20 µg/$m^3$) smoke density. The authors observed positive associations in all adults, but associations were larger in magnitude among individuals 65 years of age and older. Additionally, Wettstein et al. (2018) reported a positive association with incidence of stroke among those 65 years and older following smoke exposure. The results of Rappold et al. (2011) and Wettstein et al. (2018) indicate a need for additional exploration of: the effect of wildfire smoke exposure on cardiovascular outcomes in older individuals; cause-specific cardiovascular outcomes; and the most appropriate exposure indicator to represent wildfire smoke exposure when focusing on cardiovascular outcomes.

In addition to the outcomes examined through studies of ED visits and hospital admissions, a recent study by Jones et al. (2020) examined out-of-hospital cardiac arrests (OHCAs) attended by emergency medical services (EMSs). The study was conducted across 14 California counties where daily exposures were classified as light, medium, or high smoke density based on $PM_{2.5}$ estimated from the NOAA Hazard Mapping System. The authors reported positive associations with OHCA at multiple single day lags on heavy smoke density days (i.e., estimated smoke $PM_{2.5}$ concentrations >22 µg/$m^3$) with the strongest evidence at lag 2 (odds ratio [OR]: 1.70 [95% confidence interval (CI): 1.18, 2.45]). There was no evidence of associations when examining light or medium smoke density days.

#### 6.2.2.3 Mortality

Across the epidemiologic studies conducted that examine the relationship between short-term wildfire smoke exposure and health effects, to date, only a few U.S.-based studies examine mortality. Although the evidence base for wildfire smoke exposure and mortality from studies conducted in the U.S. is limited to a few studies, there is extensive evidence indicating a relationship between short-term $PM_{2.5}$ exposure and mortality spanning both single and multicity studies conducted in diverse geographic locations, populations with different demographic characteristics, and studies employing different exposure assessment methodologies (U.S. EPA, 2019b).

Doubleday et al. (2020) conducted the most comprehensive assessment of mortality, in a study conducted in Washington state that spanned multiple fire seasons and cause-specific mortality outcomes. Using an exposure indicator that was based on defining smoke days versus nonsmoke days, in a case-crossover analysis the authors reported evidence of a positive association for both respiratory disease (OR: 1.09 [95% CI: 1.00, 1.18], lag 0) and COPD mortality (OR: 1.14 [95% CI: 1.02, 1.26]; lag 0), but no evidence of an association for other mortality outcomes including total (nonaccidental), cardiovascular, and IHD. Unlike Doubleday et al. (2020), which focused on wildfire events and mortality in the same state, Zu et al. (2016) provided evidence to support the results of Doubleday et al. (2020) in a study that examined the relationship between wildfire smoke exposure and mortality in a study of hemodialysis patients with end-stage kidney disease (ESKD) that resided in U.S. counties near a major wildfire during the years 2008 through 2012. The authors reported a positive association with all-cause mortality for a 10 $\mu g/m^3$ increase in wildfire specific $PM_{2.5}$ that was similar in magnitude at both lag 0 (relative risk [RR] = 1.04 [95% CI: 1.01, 1.07]) and for a distributed lag of 0−1 days (RR = 1.05 [95% CI: 1.01, 1.08]), with limited evidence of an association for the other mortality outcomes examined.

#### 6.2.2.4 Uncertainties and Limitations in the Health Effects Evidence

The current state of the science with respect to the health effects of wildland fire smoke exposure stems from the large evidence base demonstrating a range of health effects, including respiratory and cardiovascular effects and mortality, in response to short- and long-term $PM_{2.5}$ exposure. Studies of wildfire smoke exposure report results that are generally consistent with this larger evidence base, but uncertainties remain in gaining a fuller understanding of the health effects of wildland fire smoke. Although this section focuses exclusively on U.S.-based epidemiologic studies, it is important to recognize it only represents a fraction of the studies conducted globally, but overall, the results of the U.S.-based studies are consistent with this broader body of evidence.

As noted in Section 6.2.1, there is variability in both the exposure assessment approach and exposure indicator employed across studies, which can complicate the interpretation of results across studies. However, even with this variability results are generally consistent across studies and health effects, specifically when examining short-term (i.e., daily) smoke exposure. While there is a general understanding of the health effects attributed to short-term smoke exposure, to date, there has been limited investigation and evidence for other exposure durations, including subdaily (i.e., <24-hour average), repeated high exposures over many days, and exposures over multiple fire seasons or years. Additional research focusing on other exposure durations can aid in informing land management strategies, such as prescribed fire; the potential health implications of smoke exposure from single wildfire events, as well as fires over multiple years; and further enhance public health messaging campaigns. Lastly, although current evidence does not indicate a difference in the health effects between ambient $PM_{2.5}$ exposure and other source-based exposures, such as wildfire smoke (U.S. EPA, 2019b), as wildfires continue to encroach upon the wildland–urban interface (WUI) the complex smoke mixture could change as structures and cars are burned, potentially resulting in different health risks.

### 6.2.3 Summary

Decades of research on the health effects attributed to exposure to ambient air pollution, specifically $PM_{2.5}$ and ozone, provide a strong evidence base for the health effects that could be observed due to short-term (i.e., daily) and long-term (i.e., months to years) exposure to wildland fire smoke. U.S.-based epidemiologic studies, which represent a fraction of the studies conducted globally, examining the health effects attributed to short-term wildfire smoke exposure have extensively examined and consistently report evidence of associations with respiratory-related health effects, including respiratory and asthma ED visits and hospital admissions, regardless of the exposure indicator used (e.g., wildfire-specific $PM_{2.5}$, smoke density, etc.). Recent studies examining short-term wildfire smoke exposure also provide growing evidence of cardiovascular effects, with more limited evidence for mortality. Overall, there are few studies that examined the health effects associated with exposure to smoke from prescribed fires, therefore, it remains unclear whether there are differential health effects from smoke from prescribed fires compared to wildfires.

Studies of wildfire smoke have not examined the health implications of long-term exposure, such as from wildfires that last multiple months (e.g., the Rough Fire) or over multiple fire seasons, but evidence from studies of long-term $PM_{2.5}$ exposure indicate these types of wildfire events could also result in mortality impacts. Additionally, although there is limited evidence of health effects attributed specifically to ozone produced from wildfire smoke, there is extensive evidence demonstrating health effects from exposure to ambient ozone exposure, indicating potential additional public health impacts from wildfire smoke.

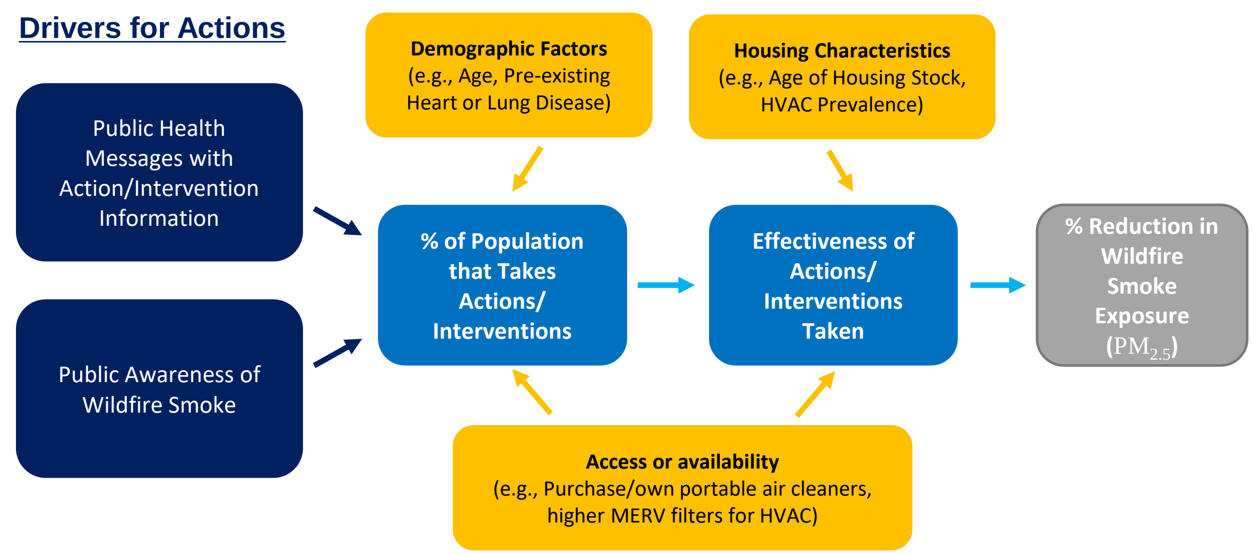
## 6.3 Mitigation of Prescribed Fire and Wildfire Smoke Exposure to Reduce Public Health Impacts

Characterizing exposure to wildfire smoke is instrumental in examining health effects, and epidemiologic studies have typically used levels of smoke or the concentration of $PM_{2.5}$ in outdoor ambient air as the exposure estimate (Section 6.2). In addition to these studies focusing on relationships between wildfire smoke exposure and health outcomes, several studies have examined individual and community actions that can be taken to reduce or mitigate exposure to smoke during wildfire events. For example, people spend most of their time indoors at home, work or school (Klepeis et al., 2001), where smoke exposure can be reduced relative to outdoors depending on factors such as building ventilation and use of air filtration (U.S. EPA, 2020c). This section describes a framework for, and the type of data needed to quantify the potential public health benefits of actions that reduce or mitigate smoke exposure. These actions, also often referred to as interventions, consist of some form of individual behavioral change, such as staying indoors with windows and doors closed or reducing activity levels; the use of personal protective measures, such as a respirator; using a portable air cleaner indoors or the extended use of a heating, ventilation, and air conditioning (HVAC) system equipped with a high efficiency particle filter; or community-level interventions (e.g., providing clean air spaces). While each of these actions can reduce wildfire smoke exposure for an individual by some percent, the overall fraction of the population taking preventative measures depends on many factors, such as population demographics, access to interventions, whether smoke is visible or can be smelled, and perceived risk of smoke exposure, all of which may also be impacted by public health messaging campaigns. Of these factors, the timing, content, and extent of public health messaging campaigns may represent a major difference in how prescribed fire and wildfire events are managed. However, whether there are differences in the percent of the population taking actions between the fire types has not been assessed.

The following sections provide an overview of a framework that captures the factors that need to be accounted for in order to estimate the potential reduction in overall smoke exposure for a population during both prescribed fire and wildfire events. Additionally, it evaluates and summarizes results from studies that provide data on how often people take action during smoke events and the exposure reduction that occurs from those actions (see Appendix A.6.2 for details on study inclusion criteria). The information presented within this section will be used to provide a crude estimate of the potential reduction in health impacts in the case study areas that could be achieved due to specific actions or interventions to reduce smoke exposure (see Section 8.3.3). However, it is important to recognize that the estimation of the potential reduction in public health impacts attributed to smoke exposure within this assessment is not meant to reflect a formal analysis of post-fire effectiveness of public health messaging by Air Resource Advisors (ARAs) deployed by the U.S. Forest Service, in combination with respective state and local air quality agencies, for either the TC6 or Rough fires.

### 6.3.1 Framework for Estimating the Impact of Actions to Reduce Smoke Exposure

Estimating potential reductions in wildfire or prescribed fire smoke exposure that a population could experience as a result of actions, or interventions, is based on a series of events and assumptions (Figure 6-4). The overall exposure reduction for a population will be determined by the likelihood and/or ability to take a particular action combined with the exposure reduction effectiveness of the action. There are multiple factors that influence both of these elements, but one major driver for any action is the awareness of the need to take action.




HVAC = heating, ventilation, and air conditioning; MERV = minimum efficiency reporting value; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

**Figure 6-4 Considerations for estimating potential reduction in wildfire smoke exposure due to actions and interventions.**

Information dissemination, specifically focusing on the potential risks of wildfire smoke exposure and actions a population can take is the initial step that can ultimately dictate whether individuals take actions to reduce exposure. However, public health messaging on its own is not enough if the proper information is not conveyed. The limited assessment of public health messaging campaigns has shown that only 14−46% of wildfire smoke related messages disseminated by government and media entities indicate the individual and administrative actions that can be taken to reduce smoke exposure (Van Deventer et al., In Press). Additionally, people may take actions to reduce exposure regardless of public health messaging campaigns as a result of general awareness of the presence of wildfire smoke (Kolbe and Gilchrist, 2009; Künzli et al., 2003). Both public health messaging and general awareness of smoke factor into the percent of the population that takes an action or institutes an intervention to reduce exposure.

Whether or not people take actions to reduce smoke exposure can depend on their knowledge of the potential impact of environmental exposures on their health (Rappold et al., 2019) as well as their personal experiences with smoke, perceptions of risk and level of self-efficacy (Hano et al., 2020). This is often a reflection of the age or underlying health status of an individual or family member. While not directly factored into an estimation of potential exposure reductions due to various actions, it is important to acknowledge that the population-level response to taking actions could vary within the population based on socio-demographic factors. Additionally, the ability to take actions depends on the accessibility and availability of interventions, such as portable air cleaners and high efficiency HVAC filters. Access and availability may depend on having the financial means to purchase interventions, but also whether programs for providing interventions exist within an area. Even low-cost interventions can have barriers to their use, such as staying indoors with doors and windows closed without air conditioning when smoke and high temperatures co-occur.

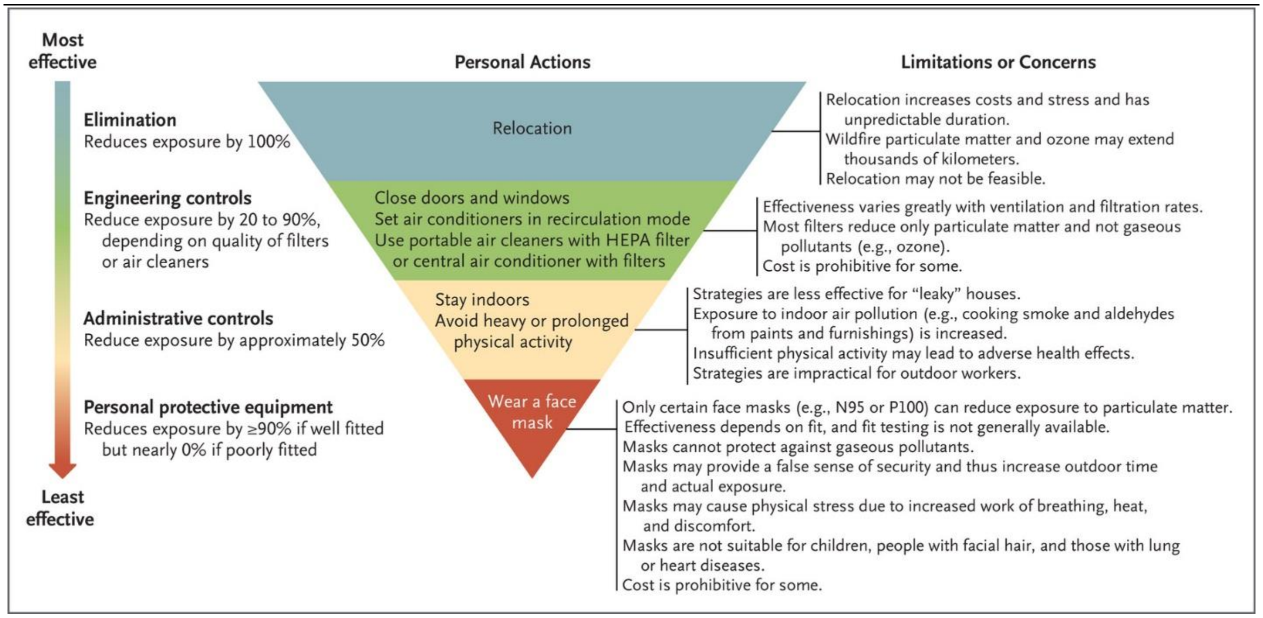
There are numerous actions people can take to reduce exposure to smoke, with a large degree of variability in the efficacy of each (Xu et al., 2020; Laumbach, 2019). The primary focus for several actions is reducing indoor $PM_{2.5}$ concentrations while at home where people spend most of their time. Housing characteristics, such as age of the home and presence and type of HVAC system, influence the infiltration of particles indoors under normal conditions, and also influence the efficacy and availability of these actions for reducing smoke exposure in homes (Joseph et al., 2020; U.S. EPA, 2020c; Davison et al., In Press). Therefore, housing characteristics of the geographic area impacted by smoke is another important factor, and if variability in the housing stock is not accounted for in some way then estimates of exposure reduction could be under- or overestimated.

Embedded within the potential actions and interventions a population within a defined geographic area may take to reduce smoke exposure are a series of operating conditions that can directly influence the overall percent reduction in smoke, specifically $PM_{2.5}$. These conditions, such as how often a building's HVAC system runs, and whether a high-efficiency filter and/or portable air cleaner is used, are important to consider when constructing potential exposure reduction scenarios. Similar to housing characteristics, the distribution of these operating conditions can vary throughout the population being examined, may depend upon public awareness of the presence of smoke, and can contribute to over- or underestimation of the overall exposure reduction of a particular action.

At each step of the process of developing scenarios to estimate the influence of actions to reduce smoke exposure there are decision points that rely on both data from published studies and assumptions regarding the population being examined. Outlining these decision points will allow for a clear articulation of the factors that influence each exposure reduction scenario and the ability to construct scenarios meant to represent the range of exposure reductions that could be experienced.

### 6.3.2 Individual and Community Actions to Reduce Smoke Exposure

In identifying the overall percent reduction in smoke exposure that can be achieved in response to public health information dissemination, the key factors to consider are the actions that can be taken at both the individual and community level and the effectiveness of those actions in reducing exposure, particularly to $PM_{2.5}$. Recent publications by Xu et al. (2020) and Laumbach (2019) provide overviews of the actions that individuals can take to reduce smoke exposure, which are delineated into four broad categories according to the hierarchy of controls traditionally used for occupational hazards (NIOSH, 2015): elimination, engineering controls, administrative controls, and personal protective equipment. As depicted in Figure 6-5, there are a range of smoke exposure reductions that can be achieved depending on the approach instituted, but for each there are limitations and concerns that should be considered. This section characterizes the broader body of studies that examined the effectiveness of information dissemination and various exposure reduction actions, which collectively provides evidence that supports the range of smoke exposure reductions that could be achieved if individuals are well informed and take the necessary steps to reduce/mitigate exposure.




HEPA = high-efficiency particulate air.
Source: Xu et al. (2020), copyright permission pending.

**Figure 6-5 Summary of individual-level wildfire smoke exposure reduction actions and effectiveness.**

### 6.3.2.1 Factors That Influence Taking Actions to Reduce Smoke Exposure

Several studies examined how awareness of smoke, whether by direct observation or through public service announcements (PSAs), can translate into a population taking exposure reduction actions. Most of the information available on the effectiveness of PSAs stems from studies conducted in California or in Australia where wildfires impact large population centers and occur on a near yearly basis. Of the available studies, all were conducted in the context of wildfire with no information currently available on the likelihood of actions taken in response to prescribed fire smoke. Studies on prescribed fire have focused on the factors governing the tolerance of smoke and optimal risk communication (Olsen et al., 2017; Blades et al., 2014), rather than exposure reduction actions taken in response to smoke.

Studies of exposure reduction actions are often conducted through retrospective surveys of communities impacted by major wildfires to determine population awareness of smoke, PSAs or other health risk communications, and the resulting actions as a function of the messaging medium (Kolbe and Gilchrist, 2009; Mott et al., 2002), content (Sugerman et al., 2012), and the characteristics of the community (Kolbe and Gilchrist, 2009). These studies have investigated the impact of population demographics (e.g., age, gender, income level, etc.), pre-existing conditions, and experiencing symptoms on the type and extent of exposure reduction action taken.

Across studies that examined PSAs, in most communities the awareness of PSAs was high (74−88% of those surveyed recalled a PSA) with many people (43−98%, Table A.6-2) taking some exposure reduction action in response to a PSA, but the most effective method of communication varied by community. Television was the most effective communication medium in studies conducted in San Diego [77%; Sugerman et al. (2012)] and Australia [68%; Kolbe and Gilchrist (2009)] while radio was the most effective medium in a rural tribal community in northern California (Mott et al., 2002). However, in this community a wide variety of information sources (e.g., the medical establishment, friends and family, and the workplace) were recalled in greater frequency than television, demonstrating the impact of the community type on the most effective method of risk communication.

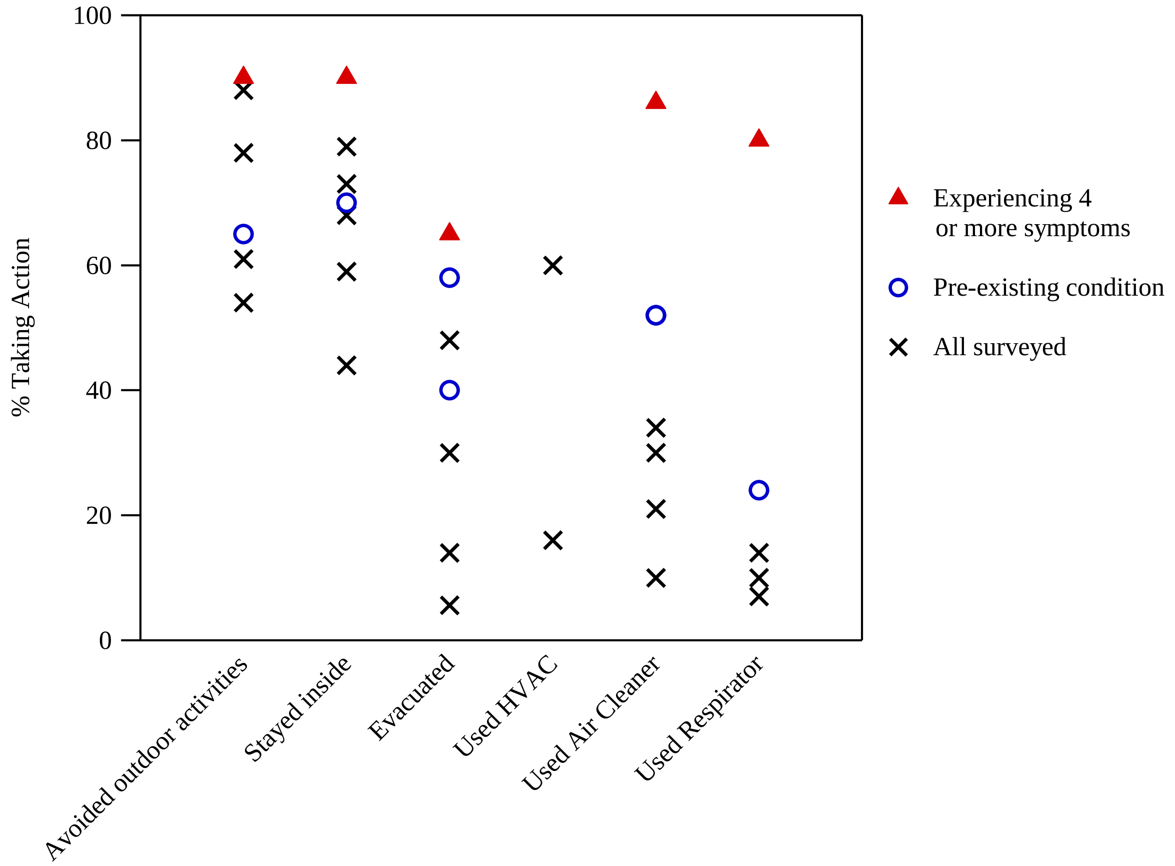
When considering the implications of the demographic composition of a population, older adults were less likely to be aware of PSAs with only 58% of those over 75 years of age aware of the PSA compared to 74% for the entire population (Kolbe and Gilchrist, 2009). Those with pre-existing conditions (81%) were also found to be slightly less likely than those without a pre-existing condition (85%) to be aware of PSAs (Mott et al., 2002). While it is important to be aware of the message, message comprehension is also extremely important when considering whether individuals take the necessary actions to protect themselves. Sugerman et al. (2012) observed that message comprehension was reduced in those that did not speak the primary language or when the message was too technical in nature (e.g., stay inside vs. run HVAC system more often).

Overall, across studies it was found that most people aware of a PSA took some action to reduce exposure [66−98%; Sugerman et al. (2012); Kolbe and Gilchrist (2009); Mott et al. (2002)]. The awareness of smoke also prompted people to act. For example, in Australia of the 76% of the population that took an exposure reduction action 43% did so due to the PSA and 28% due to the presence of smoke (Kolbe and Gilchrist, 2009). Furthermore, the percentage of people reducing outdoor activities, closing doors and windows, and evacuating was similar between those responding to the smoke and those responding to a PSA (Kolbe and Gilchrist, 2009). The more technical actions were much more likely to be used by those aware of the PSA than those that were not, like using a mask (8.1% aware of PSA vs. 1.3% not aware) or using ceiling fans [10.5% aware of PSA vs. 2.9% not aware; Kolbe and Gilchrist (2009)].

The most commonly used actions were those that are easiest to carry out, including reducing or avoiding outside activity, and staying inside or closing windows and doors (Figure 6-6, Table A.6-2). On average for the total surveyed population, the least likely actions were using an air cleaner (10−34%) or respirator [7−14%;. Sugerman et al. (2012)] found that more technical actions (e.g., use home air conditioning, use HEPA air filtration, wear N95 mask during ash clean up) were least likely to be done in part due to a poor recall of the PSA and a difficulty understanding the PSA. Accessibility to measures that can reduce exposure, such as an HVAC system, air cleaner or respirators/masks, while not formally characterized in any of the studies evaluated, may significantly impact the probability of an individual taking an exposure reduction action.

As depicted in Figure 6-6, there is a wide distribution in the percentage of each population taking action to reduce or mitigate smoke exposure, which is in large part due to the different populations surveyed. People actively experiencing symptoms due to wildfire smoke were much more likely to take an action than the general population. This is most striking for actions that require equipment, like air cleaners or respirators. For example, Rappold et al. (2019) reported that 86% of people with four or more symptoms used an air cleaner versus 24% of the average population (averaged across all studies).

Most studies provided some indication of the smoke concentration and duration in the community [e.g., from Mott et al. (2002)] which reported $PM_{10}$ (particulate matter with a nominal aerodynamic diameter less than or equal to 10 μm ): 2 days $PM_{2.5}$ >425 μg/m$^3$ and 15 days >128 μg/m$^3$, assuming $PM_{2.5}$ is 85% of $PM_{10}$ concentrations as detailed in Lutes (2014). However, inconsistent reporting prevents the determination of a clear association between smoke exposure (duration or peak concentration) and the probability of taking a particular action. The level and duration of smoke exposure are likely major determinants in what actions a community will take and important factors to be considered in future studies.




HVAC = heating, ventilation, and air conditioning.

Note: All surveyed is from the general population indiscriminate of health history or status. Data presented is from Rappold et al. (2019); Richardson et al. (2012); Sugerman et al. (2012); Kolbe and Gilchrist (2009); Mott et al. (2002).

**Figure 6-6 Percentage of the population taking a specific exposure reduction action as a function of the characteristics of the surveyed population.**

### 6.3.2.2 Effect of Actions/Interventions on Reducing $PM_{2.5}$ Exposure Concentrations

The effectiveness of various actions or interventions in reducing $PM_{2.5}$ exposure concentrations has been quantified in several studies. However, studies that examined $PM_{2.5}$ exposure reduction actions during wildfire or prescribed fire smoke periods were limited. More studies examined the effect of actions for typical ambient $PM_{2.5}$ conditions. Most relevant studies evaluated the effectiveness of portable air cleaners and more efficient HVAC system filters with residential $PM_{2.5}$ monitoring with a few additional studies conducting modeling of residential buildings to estimate effectiveness (see Table A.6-3). Studies of nonresidential building types were limited to a few studies focusing on office buildings, with no other building types (e.g., schools) examined. Studies that examined the effectiveness of masks for reducing exposure to particles in air have primarily been conducted for occupational exposure and other purposes (Allen and Barn, 2020), and not specifically for examining their effect in reducing smoke exposure within the general population.

Reviews by Xu et al. (2020) and Laumbach (2019) compare percent reductions for various actions that could be taken to reduce or mitigate smoke exposure. Elimination of smoke exposure can be achieved by relocation (exposure reduction = 100%), while engineering controls such as closing windows and doors or indoor air filtration can also be effective (20−80% exposure reduction), as are administrative controls such as staying indoors and avoiding outdoor activities (~50% exposure reduction). Additionally, both Xu et al. (2020) and Laumbach (2019) noted that wearing N95 or P100 masks can be 90% effective or more, but only if properly fitted along with other limitations (e.g., not suitable for children). The results reported in Xu et al. (2020) and Laumbach (2019) are generally consistent with the levels of effectiveness for the different actions reported in recent studies.

U.S. EPA (2018) reviewed residential measurement studies that used portable air cleaners and central HVAC system filters to reduce indoor $PM_{2.5}$ exposures overall, not $PM_{2.5}$ specific to wildfire smoke. Portable air cleaners were found to substantially reduce indoor concentrations of PM of both indoor and outdoor origin, often reducing indoor $PM_{2.5}$ concentrations by around 50% on average.

Residential measurement studies that examined portable air cleaner effectiveness in homes during wildfire smoke events (Barn et al., 2008; Henderson et al., 2005) also reported a similar percent reduction in indoor $PM_{2.5}$ concentrations with the elevated outdoor $PM_{2.5}$ concentrations during these events. Barn et al. (2016) also reviewed many of the same studies as U.S. EPA (2018) and concluded that portable air cleaners can reduce indoor $PM_{2.5}$ concentrations by 32−88% and recommended their use during fire events.

U.S. EPA (2018) also noted a few residential measurement studies that showed higher efficiency central HVAC system filters such as those rated minimum efficiency reporting value (MERV) 13 or above can reduce indoor $PM_{2.5}$ concentrations. Singer et al. (2017) reported a 90% reduction in $PM_{2.5}$ using HVAC filtration with high efficiency MERV filters in a single test house in California during typical ambient $PM_{2.5}$ concentrations, which was comparable to running a portable air cleaner in the home. However, results from a recent study by Alavy and Siegel (2020) showed actual in-home effectiveness of HVAC filtration for $PM_{2.5}$ was much lower (average ~40%) and varied widely across homes even for filters with the same MERV rating depending on the home. Filter performance was strongly linked to home- and system-specific parameters including ventilation rate and system runtime.

Of the studies evaluated, Reisen et al. (2019) is the only available residential measurement study that examined the effectiveness of closing windows and doors during a smoke event. However, the study only included four homes in Australia that experienced smoke due to a prescribed fire. Simple infiltration modeling of the measurements showed that remaining indoors with windows and doors closed reduced exposure to peak $PM_{2.5}$ concentrations by 29 to 76% across the homes and that a tighter house, in terms of reduced ventilation, provided greater protection against particle infiltration.

A comprehensive residential modeling study by Fisk and Chan (2017b) compared central HVAC system filtration and portable air cleaners for six different home type scenarios during a wildfire smoke event in California. The combined effect of continuous HVAC fan use with a high efficiency (MERV 12) filter and continuous portable air cleaner was most effective (62% reduction in $PM_{2.5}$), while continuous portable air cleaner use in homes without forced-air HVAC systems provided 45% reduction in $PM_{2.5}$ concentrations.

While most of the studies conducted focus on examining the effectiveness of interventions in residential locations, a few studies examined the effectiveness of HVAC systems and filters in office buildings during wildfire smoke events. Stauffer et al. (2020) compared offices with and without portable air cleaners during a wildfire season. They reported 73 and 92% reduction in $PM_{2.5}$ concentrations indoors with portable air cleaner use for daytime and nighttime, respectively. Pantelic et al. (2019) reported a 60% reduction in $PM_{2.5}$ for a mechanically ventilated office building and higher efficiency filters compared to a naturally ventilated building during a wildfire.

Fisk and Chan (2017a) conducted a modeling study comparing improved filtration using filters in residential forced-air systems and/or portable air cleaners for homes and higher efficiency filters in commercial buildings in three U.S. cities (Los Angeles, Houston, Elizabeth, NJ) for ambient $PM_{2.5}$ concentrations. Additional higher efficiency filtration in other buildings only slightly reduced overall $PM_{2.5}$ exposures due to the amount of time spent in these locations compared to at home.

In summary, although limited in number, studies that examined the effectiveness of actions or interventions to reduce $PM_{2.5}$ exposure provide relevant data for considering the potential implications of public health messaging campaigns and the most effective actions to recommend to the public to reduce exposure to wildfire smoke (see Table A.6-3). Portable air cleaners were shown to reduce residential indoor $PM_{2.5}$ concentrations from ~40−90%, depending on the study and home characteristics. Increasing filtration efficiency in residential forced-air systems and/or running the system more/continuously can also reduce indoor $PM_{2.5}$ concentrations by a similar percent, but data from these studies were more variable between homes and efficiency of the filters. The data also suggest office buildings with high-efficiency filters in HVAC systems or that use portable air cleaners can achieve a similar reduction in indoor $PM_{2.5}$ concentrations (~60−90%) as homes. Lastly, there is limited data to fully assess the effectiveness of only closing windows and doors and staying inside as a means to reduce wildfire smoke exposure.

### 6.3.3 Estimating the Overall Exposure Reduction to Wildfire Smoke for Individual-Level Actions

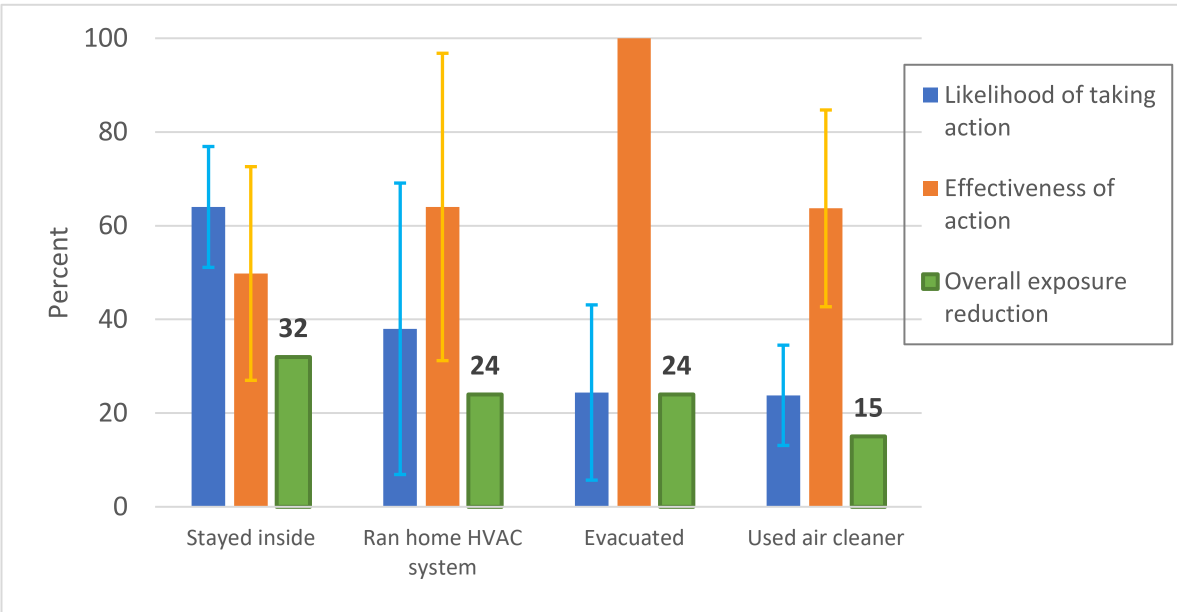
Although the available data on individual and community actions that can be taken to reduce smoke exposure is currently limited, the data detailed within this section provides information on many of the factors to consider that are depicted in Figure 6-4 for estimating the potential impact of actions/interventions on reducing $PM_{2.5}$ exposure from wildfire smoke. An approximation of the overall percent reduction in $PM_{2.5}$ exposure for a population that could be achieved by individual-level actions can be estimated by combining the data on the likelihood of taking actions in response to smoke with the effectiveness of the various actions (Table 6-1). However, it is important to recognize that across the studies evaluated there was a wide range of data on both the likelihood and effectiveness of exposure reduction actions (see, Table A.6-2 and Table A.6-3). Therefore, the values reported in Table 6-1 represent the average with standard deviation across studies for likelihood and effectiveness of the different actions and interventions.

**Table 6-1 Summary of data available for various exposure reduction actions.**

| Exposure Reduction Action | Likelihood of Taking Action in Response to Wildfire[a] Mean ± SD | Effectiveness of Action[b] Mean ± SD | Average Overall Exposure Reduction[c] |
|---|---|---|---|
| Reduced activity | 70.3% ± 15.5 | No data | -- |
| Stayed inside | 64.0% ± 12.9 | 49.8% ± 22.8 | 31.8% |
| Ran home HVAC system | 38.0% ± 31.1[d] | 64.0% ± 32.8 | 24% |
| Evacuated | 24.4% ± 18.7 | 100% | 24% |
| Used air cleaner | 23.8% ± 10.7 | 63.7% ± 21.0 | 15% |
| Used respirator | 10.3% ± 3.5 | No data[e] | -- |

HVAC = heating, ventilation, and air conditioning; SD = standard deviation.
[a]From studies in Table A.6-2 for respondents regardless of health history or status.
[b]From studies in Table A.6-3.
[c]Average likelihood of taking the action multiplied by the average effectiveness of the action.
[d]May include the use of other air conditioning systems in addition to HVAC systems.
[e]No data available on the effectiveness of respirators for reducing wildfire smoke exposure.

For each exposure reduction action, the average overall percent exposure reduction, at the population-level, was calculated by multiplying the average likelihood of taking the action by the average effectiveness of the action. Although simplistic, this approach provides an initial comparison that shows the more effective actions are generally less likely to be used, resulting in a lower overall exposure reduction (Figure 6-7). For example, the data on portable air cleaner use showed an average ~64% reduction in $PM_{2.5}$ but the likelihood of using them was ~24% on average, resulting in an overall exposure reduction of ~15%. The exposure reduction action with the highest average overall percent reduction was staying inside (~32%), due to the greater likelihood of people taking this action (~64% on average) and its relative effectiveness (~50% on average). It should be noted that combining these two types of study data assumes a reasonable match between the interventions reported in the survey studies of PSA effectiveness and those evaluated in the effectiveness studies, which may not be appropriate in all cases.




HVAC = heating, ventilation, and air conditioning; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

**Figure 6-7 Comparison of estimated percent overall $PM_{2.5}$ exposure reduction by action.**

### 6.3.4 Uncertainties and Limitations in Estimating Exposure Reduction to Wildland Fire Smoke

While it is clear from Figure 6-7 that there are actions that can be taken at the individual level that could substantially reduce overall population exposure to wildfire smoke, there are multiple assumptions and limitations that should be considered in the process of using this information to estimate the potential public health benefit of messaging campaigns. The studies conducted to date examining actions and interventions to reduce wildfire smoke exposure, specifically $PM_{2.5}$, have been conducted over a limited geographic scale, and, as such, may not be transferrable across locations. However, the limited geographic scale of available studies could be accounted for by including location specific information in an analysis, such as detailed information on the housing stock (e.g., age, type of HVAC, etc.), population demographics, and community characteristics (e.g., urban vs. rural). Additionally, the average overall exposure reductions presented do not account for the likelihood that taking actions may differ significantly between wildfire and prescribed fire smoke events, due to potential differences in public health messaging campaigns for each fire type (e.g., PSAs in preparation for prescribed fires are not uniform across locations). These potential differences between wildfire and prescribed fire may also include differences in the effectiveness of an action or intervention due to variability in $PM_{2.5}$ concentrations. Specifically, the effectiveness may be reduced at the very high $PM_{2.5}$ concentrations associated with large wildfire events.

Perhaps the greatest difference in potential smoke exposure reductions can be attributed to the different level of public awareness of smoke for the two different types of fires. Smoke from prescribed fires may be present for a short duration, as little as several hours, and at lower concentrations that may not be noticeable. Alternatively, wildfires may lead to prolonged high smoke concentrations with noticeable odor and visibility impacts. Wildfires are often reported on by the local news media, which may include public service announcements about actions to reduce smoke exposure. Additionally, most major wildfire incidents have an ARA that develops and disseminates information on smoke forecasts, air quality, and messaging to address public health concerns. The ARA generates daily smoke reports that are posted online on InciWeb [https://inciweb.nwcg.gov; NIFC (2021)], state smoke blogs, and on fire information boards through impacted communities. Prescribed fires are not as widely publicized and depending on the state or local regulations may be conducted without any notifications or alerts to the surrounding community. Therefore, public awareness of prescribed fires may be very limited, greatly reducing the potential for exposure mitigation actions to be taken.

Another difference is that wildfires and prescribed fires often occur at different times of the year when residential ventilation rates may vary. In the study areas and many parts of the western U.S., wildfires largely occur during July through October (Jaffe et al., 2020; Ryan et al., 2013). Prescribed fires are often done in the late fall or early spring during cooler weather (see Section 3.2.2.1), while pile burns of mechanically thinned biomass are typically done in the winter months. These different seasons of the year for the fire types may have ambient conditions that lead to different behaviors with respect to home ventilation (Marr et al., 2012; Yamamoto et al., 2010). In areas where residential air conditioning systems are not prevalent, wildfires may frequently coincide with time periods when ventilation rates may be highest as windows and doors would be opened to cool the indoor environment. In contrast, in areas where air conditioning systems are prevalent, prescribed fires may coincide with time periods when ventilation rates may be greater due to window and door opening during the more temperate months.

In addition to the differences in smoke exposure between fire types noted above, there are also data gaps that complicate the ability to quantitatively estimate the overall exposure reduction that could be achieved. Within this assessment, a crude approach is taken to estimate the potential public health impact of different actions and interventions to reduce smoke exposure, but it does not account for the fact that in reality a combination of these actions or interventions will be employed across the population (see Section 8.3.3). As depicted in Figure 6-4, a real-world estimation of the overall percent reduction in smoke exposure requires multiple pieces of data including demographic data, housing characteristic data, and data on access or availability to various actions or interventions. Therefore, each of these pieces of data will vary depending on geographic location, demonstrating that a one-size fits all approach is not ideal, but can provide an estimation of the potential public health implications of reducing smoke exposure using different actions or interventions as presented within this assessment. In the future, as more data is collected on how people respond to wildfire smoke, such as through the SmokeSense app [https://www.epa.gov/air-research/smoke-sense-study-citizen-science-project-using-mobile-app; U.S. EPA (2020b)], it could be possible to more fully account for and quantify the actions taken by individuals affected by smoke through data analysis or exposure modeling, and subsequently assess the potential overall smoke exposure reduction for a population.

## 6.4 Ecological Effects Attributed to Wildfire Smoke and Deposition of Pollutants

Wildfire smoke and the deposition of pollutants on plants and animals in terrestrial and aquatic environments can have a range of effects. For example, pathogenic fungi have been shown to be aerosolized on smoke particulates and transported downwind from wildfires. Forest pests can be stimulated by smoke where it serves as an attractant to pyrophilous beetle species that are adapted to reproduce in the downed lumber and freshly burned wood following a fire (Lesk et al., 2017; Hart, 1998; Evans, 1971). In addition to effects on lower trophic levels, smoke effects have also been documented to occur in vertebrates. After the fires of 1988 in Yellowstone National Park, for example, hundreds of large mammals, including elk, moose, mule deer, and bison were found dead: autopsy evidence suggested that smoke inhalation killed nearly all these animals (Singer and Schullery, 1989). Smoke inhalation has also been associated with mortality in raptors as a result of promoting subsequent fungal infection in lungs following smoke exposure (Kinne et al., 2010). While numerous adverse effects from wildfire emissions have been documented, smoke can also have a stimulatory effect on the environment (McLauchlan et al., 2020). The following sections more fully characterize the direct effects of wildfire smoke and deposition of pollutants on plants and animals in terrestrial and aquatic environments.

### 6.4.1 Particulate Matter (PM)

Wildland fire is an increasing source of particulate matter emissions (see CHAPTER 5), a substantial fraction of which is represented by particulate matter, specifically $PM_{2.5}$, which have been shown to have a variety of impacts on the environment (Bond and Keane, 2017). While this section will focus on aquatic and ecological effects, it's important to recognize the potential climatological impact of wildfire smoke. Particulate matter generated from wildfires has been shown to affect cloud cover and ice nucleation and interact with solar radiation through absorption and scattering. Specifically, the deposition of the $PM_{2.5}$ component black carbon has been shown to increase soil temperature through absorption of solar radiation (U.S. EPA, 2012). This is noteworthy in Pacific Northwest forests given the increasing rate and quantity of black carbon deposition in today's unprecedented fire regime because increased soil temperature is associated with concurrent decreases in tree growth which is a precursor to tree mortality. In contrast, certain highly reflective PM components in the atmosphere can scatter incoming solar radiation with much of that energy returning to space and can have an overall cooling effect on the climate (U.S. EPA, 2019b). Two of the better studied aspects of the effects of wildfire smoke on the environment include the transport of microorganisms on smoke particles following a fire and smoke-stimulated flowering/seed germination seed release.

#### 6.4.1.1 Transport of Bacteria and Fungi from Soil and Plants through Smoke

A relatively recent advancement in fire ecology includes the nascent field of pyroaerobiology, which considers the living component of smoke particles generated from wildfires; specifically, microbes aerosolized and transported on particles by wildland fire (Hu et al., 2020; Kobziar and Thompson, 2020; Kobziar et al., 2018). Recent studies have documented elevated concentrations of bacteria and fungi in smoke from burning of woody materials (Mirskaya and Agranovski, 2020) and in smoke from coniferous forest wildfires (Kobziar et al., 2018) through the collection of microorganisms on passive samplers oriented to the wind direction. The authors showed that microbial counts following the fire were significantly elevated above ambient conditions and decreased with distance from the fire's flaming front. It has been hypothesized that these microorganisms could represent an infectious risk to the public (Kobziar and Thompson, 2020) while also serving as an important inoculum for reseeding the soil flora following a fire event.

#### 6.4.1.2 Smoke-Stimulated Flowering/Seed Germination and Seed Release

In their review of the ecological effects of fire, Bond and Keane (2017) noted that flowering is common among perennial grasses and herbs, some species of which only flower when cued by smoke (Chou et al., 2012). Wildfire smoke also stimulates germination in soil seedbanks for many species adapted to fire-prone forests and shrublands such as those in California (Keeley et al., 2005). In such environments, seedling recruitment from seed banks is one of the primary means of regeneration following a wildfire event. In fire adapted environments, germination is the result of either heat shock or exposure to combustion products in smoke. However, germination can also be stimulated in some fire adapted species through direct deposition on the seed or as a result of smoke binding to soil particles and subsequent aqueous or atmospheric transfer to seeds (Keeley et al., 2005). While dozens of individual chemicals and particulate matter comprise wildfire smoke, Keeley and Fotheringham (1997) showed that it is the nitrogen oxides ($NO_X$) present as trace gases in smoke that are responsible for seed germination.

### 6.4.2 Effects of Ozone ($O_3$) from Fires

Wildfire smoke consists of numerous components (see CHAPTER 4 and CHAPTER 5), including volatile organic compounds (VOCs) and $NO_X$ which can increase ozone production downwind following a wildfire event (Jaffe and Wigder, 2012). Because VOCs are ubiquitous in most geographic locations, it is generally thought that $NO_X$ concentrations are the rate-limiting factor to ozone formation. The amount of $NO_X$ produced during a wildfire is a function of the N content of the fuel, which varies by species, age and type of ecosystem, and the intensity of the burn. Higher temperature fires tend to produce more oxidized forms of N than lower intensity burns, and therefore are thought to produce more of the $NO_X$ precursors available for ozone production (Jaffe and Wigder, 2012). Lower intensity burns tend to produce more oxygenated VOCs. The difference in ozone concentrations that can occur depending on fire type is reflected in the different hypothetical scenarios examined in the case studies presented within this assessment (see CHAPTER 5).

There is overwhelming evidence linking tropospheric ozone with reductions in growth and productivity in both agricultural and natural ecosystems (U.S. EPA, 2020a). Ecological effects of ozone can be observed across multiple scales of biological organization, from cellular to individual organism to the level of communities and ecosystems. Ozone can affect both aboveground and belowground processes leading to changes in productivity, carbon sequestration, biogeochemical cycling and hydrology.

At the plant level, ozone enters the leaves through stomates, and quickly disassociates in the leaf apoplast into hydrogen peroxide ($H_2O_2$), organic radicals, and other reactive compounds that damage cellular membranes (Wohlgemuth et al., 2002; Hippeli and Elstner, 1996). Through both direct effects on stomatal regulation (Grulke, 1999) as well as chloroplast degradation, ozone can decrease photosynthesis and metabolism (Matyssek and Innes, 1999). Reductions in photosynthesis and overall carbon assimilation leads to decreased growth, but also can result in a shift in allocation of carbon resources within the plant, particularly to roots. These shifts in carbon allocation can lead to a change in the physiological functioning of the plant, including changes in gene regulation (U.S. EPA, 2020a; Andersen, 2003).

The direct effects of ozone on carbon assimilation and plant growth can subsequently alter the competitiveness of individuals in ecosystems. A reduction in carbon allocation to roots can alter rhizosphere interactions and symbiotic associations, both potentially leading to changes in nutrient uptake (U.S. EPA, 2020a). Changes in nutrient uptake therefore can lead to further reductions in growth, and to a change in the competitive stature of the plant. Because not all species are equally susceptible to ozone, there is often a shift in the competitive structure of ecosystems exposed to ozone, with sensitive species dropping out and ozone tolerant species becoming more competitive. Through these direct and indirect effects, both ecosystem structure and function can be altered by ozone stress downwind of a wildfire.

Ozone also influences the susceptibility of natural ecosystems to future wildfire. Ozone stress often results in early senescence of leaves, which can increase fuel load in conifer forests such as ponderosa pine that shed older leaf whorls in response to ozone stress (Miller et al., 1982). Ozone sensitive species are also more susceptible to other stresses, such as insects and pathogens, increasing tree mortality and potentially increasing the fuel load in stressed ecosystems. Since ozone tends to reduce carbon allocation to roots, ozone stressed plants also can become drought stressed, further increasing their susceptibility to other stresses and to wildfire. This can be a positive feedback loop in that as fire occurs, ozone is produced in smoke, potentially leading to susceptibility in future fire events. In addition to ozone, many studies have documented the release of hazardous organic and inorganic chemicals from combustion of biomass through wildfire and there is a vast literature on the toxicity of organic chemicals and heavy metals on plants and animals. There are, however, no studies available reporting demonstrable ecological effects from hazardous pollutants released or generated from wildland fire.

### 6.4.3 Atmospheric Deposition of Ash

The most immediate effect of wildland fire on the land surface is the removal of vegetation and the subsequent deposition of a layer of charcoal or ash (De Sales et al., 2019). Ash is the particulate residue that consists of mineral and charred organic materials formed when carbon fuels are burned (Bodi et al., 2014). Characteristics of ash are affected by the type of fuel burned and intensity of combustion, with low-intensity fires yielding ash of greater organic content and hotter fires resulting in more mineralized material. In forested environments, the mass of ash deposition following a fire can range from 2−9% of woody biomass (Raison, 1979).

Ash that is deposited on the ground is incorporated into soil where vegetation has burned. Given its high mobility, however, ash is also readily transported downwind and downstream where it can influence habitats far removed from areas burned by wildfire. Ash deposition is becoming an increasingly common input into ecosystems and it can have a dramatic effect on the biogeochemical cycling of nutrients and minerals in forested soils. This section considers the ecological effects of ash on soil chemistry and structure, nutrient flux, microbial activity, and plant growth.

#### 6.4.3.1 Soil Chemistry and Structure

Ash deposition following wildfire can profoundly change soil characteristics. In a study of ion release from burning plant material, Grier and Cole (1971) demonstrated greatly increased concentrations of ions entering the soil, which were adsorbed in the uppermost soil horizons and caused major chemical changes such as the influx of basic ions increasing soil pH. In a study of wildfire sites in California, Ulery et al. (1993) showed that ash deposition raised soil pH by as much as 3 pH units (to pH 10.5) compared with unburned soil. More basic pH increases the solubility of soil organic carbon (Andersson et al., 1994) and increases the number of binding sites in soil that can hold cationic micronutrients (Raison, 1979).

The physical deposition of ash can act to increase soil water repellency, preventing the infiltration of meteoric precipitation (Doerr et al., 2000) and decreasing the potential for nutrient leaching. Another consequence of ash deposition on soil structure is an increase in bulk density, which is the soil mass divided by the bulk volume of the sample ($g/cm^3$). The bulk density of soil increases with ash deposition because soil aggregates collapse and the ash clogs pore-space voids, both of which serve to decrease soil porosity and permeability (Verma and Jayakumar, 2012). Factors like increased soil hydrophobicity and increased density that limit the infiltration of meteoric water would help to retain otherwise leached soil nutrients.

#### 6.4.3.2 Stimulation of Microbiological Activity and Plant Growth

Although it is widely accepted that fire stimulates microbial activity (Bodi et al., 2014), most research on wildfire's effect considers soil heating only where, in extremely hot fires, sterilization of the upper soil layers can occur (Mataix-Solera et al., 2009). Far fewer studies address the effects of ash deposition on soil microbiota and nutrient processing. Compared to the growth of fungal organisms that would occur at lower soil pH, Jokinen et al. (2006) suggested that the increased soil pH and nutrient and carbon availability from ash deposition stimulated bacterial respiration. Bacteria proliferate more quickly than fungi and their ability to capitalize on a new carbon pool, such as ash-mobilized organic carbon, would favor bacterial growth suggesting an inhibitory effect of ash deposition on fungal microflora. Mycorrhizal fungi, however, have a symbiotic relationship with plants that depends on the latter's ability to produce carbohydrates through photosynthesis and share sugars with the fungus. In this relationship, plants receive water and nutrients from the soil by the extensive network of fungal mycelial hyphae. The plant's provision of carbohydrates to mycorrhizae makes this group of fungi competitive with bacteria in an otherwise challenging post-fire environment for fungal organisms.

New tree growth in burned forests is highly dependent upon mycorrhizal symbiosis and the fungal colonization of burned areas is relatively well documented. In a study of burned pine forests in northern California, Grogan et al. (2000) found that wildfire disturbance resulted in marked changes in mycorrhizal community composition and a significant increase in the relative biomass of mycorrhizal-ascomycetous fungi. Additionally, in an experiment to examine the effects of ectomycorrhizal colonization and fire on the growth of Bishop pine seedlings (*Pinus muricata*) in northern California, Peay et al. (2010) showed that the percent nitrogen in needles was greatest in treatments with an ectomycorrhizal inoculum regardless of whether ash was added to soil. These results underly the critical relationship of pine forests and their dependence on mycorrhizal associations.

Immediately downwind of fires, larger particles of ash are deposited onto vegetation with a concomitant observable soiling of leaves, which can adversely affect photosynthesis and plant growth. Nutrients may be released from combustible fuels after fire and transported as ash by atmospheric deposition to stimulate vegetation growth (Bodi et al., 2014). The amounts of calcium, nitrogen, phosphorous, potassium, magnesium and sulfur released by burning forest vegetation are elevated in relation to both the total and available quantities of these elements in soils (Raison and McGarity, 1980; Raison, 1979). The addition of nutrients in ash tend to stimulate plant growth although germination may be inhibited by deposited ash, due perhaps to ash's hydrophobicity and osmotic pressure excluding water from the seed, the presence of toxic elements in ash, and/or elevated pH (Bodi et al., 2014).

Nitrogen is among the most important nutrients that can stimulate plant growth. Forested systems rely on cycling the nitrogen locked in dead plant matter into more bioavailable forms. Compared to the biological decay of plant remains, burning rapidly releases nutrients into a plant-available form. Nitrogen from wildfires can represent over 30% of nitrogen deposition in forested systems of the Pacific Northwest (Koplitz et al., In Press) and growth of the predominant forest tree species (Douglas fir, *Pseudotsuga menziesii*) in the Pacific Northwest is stimulated by nitrogen deposition. However, too much nitrogen can be problematic and lead to nitrogen inputs exceeding the critical nitrogen load in Northwest forests and ultimately decreased tree survival.

#### 6.4.3.3 Ash Deposition and Water Quality

The aerial transport and deposition of materials in smoke and ash may also affect downwind water quality. Increased runoff of ash, sediments, and chemical constituents following fire appear to be the dominant mechanism by which water quality is affected (see Section 7.3.3.2.5 for further discussion of fire effects on water quality, including potential effects on drinking water). Nevertheless, it is logical to assume that some material could be deposited in wet or dry form onto the surfaces of downwind water bodies, such as streams, lakes or reservoirs, or deposited on unburned terrestrial surfaces and subsequently moved via overland or subsurface flow to water bodies. Post-fire increases in nutrient deposition (Ranalli, 2004; Koplitz et al., In Press), and wind dispersion of ash, nutrients, and sediments (Roehner et al., 2020; Bodi et al., 2014) are suggestive of such a mechanism.

Though studies measuring this phenomenon are limited, several have reported water quality changes potentially linked to aerial transport of materials from fires (Earl and Blinn, 2003; Lathrop, 1994; Spencer and Hauer, 1991). For instance, Earl and Blinn (2003) found higher nutrient concentrations in an unburned watershed in southwestern New Mexico, associated in time with a nearby fire. The authors suggested that aerial transport of nutrients from the fire was likely responsible. Initiating sampling within hours of a fire, Spencer and Hauer (1991) observed spikes in nitrogen and phosphorus in stream water, before returning to background levels within several days to weeks. The authors concluded nitrogen from the smoke diffused into the surface water, while phosphorus leached from ash deposited directly into the waterbodies. Nitrogen volatilizes at lower temperatures than phosphorus, likely explaining the differences in method of transport of these two nutrients.

### 6.4.4 Uncertainties and Limitations in the Ecological Effects Evidence

There are considerable uncertainties and limitations in understanding the ecological effects of smoke and ash on plants and animals. Ultimately ecosystems have adapted to fire regimes, but an understanding of fire's immediate ecological effects are limited by a dearth of studies on the direct ecological effects of smoke and ash. The influx of fire-liberated nutrients and hazardous pollutants on terrestrial and aquatic receptors is just beginning to be investigated and the time frame over which fires influence air and water chemistry is an area that warrants further investigation.

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# CHAPTER 7 ECOLOGICAL, WELFARE, AND OTHER DIRECT DAMAGES OF FIRE AND SMOKE

## 7.1 Introduction

The primary focus of this assessment is a quantitative analysis of the smoke impacts, both air quality and health, from wildland fires. As detailed in the conceptual framework outlined in CHAPTER 2, in the process of examining the trade-offs between prescribed fire and wildfire it is also important to consider the potential effects, both positive and negative, of the fire itself. While in this assessment it is not possible to quantify these effects due to a dearth of location specific data, the qualitative characterization of these additional effects helps add context to the overall examination of the trade-offs of smoke impacts due to different fire management strategies.

This chapter discusses the direct fire damages (value of economic loss) that are often experienced as a result of wildland fire. As detailed in CHAPTER 6 and quantitatively examined in CHAPTER 8, the health effects and overall population impacts of smoke exposure are well characterized. However, in addition to the potential health hazards of smoke to the general population, fire fighters are also subjected to smoke exposure and other hazards in the process of trying to control and suppress a wildland fire (Section 7.2).

While there are ecological benefits to fire (see CHAPTER 3), severe wildfires can adversely impact ecosystems and lead to significant effects on public welfare and incur societal costs as listed in Table 7-1, and discussed below. In considering the costs incurred due to wildfires, preparedness, mitigation, and suppression efforts are included, along with numerous losses that have significant impacts on society. Section 7.3, provides a broad discussion of these additional effects often experienced due to wildfires.

## 7.2 Wildland Firefighter Exposure to Smoke during Prescribed Fires and Wildfires

This section is a brief summary of the inhalation health hazards and management implications to wildland firefighters exposed to smoke pollutants at wildfires and prescribed fires. The discussion focuses on exposures to smoke from the combustion of natural fuels (with mention of soil dust) but does not consider smoke exposures from the burning of man-made products encountered by structural and wildland firefighters at wildland–urban interface (WUI) fires, or airborne hazards resulting from fires burning across polluted soils.

Similar to the population as a whole (see CHAPTER 6), smoke is both a short-term acute irritation and a long-term chronic health hazard. In the past, firefighters believed smoke was only an inconvenience, irritating the eyes and nose, causing coughing, and occasionally causing nausea and headaches. Many of the exposure limits are established to prevent acute health effects. However, there is evidence there may be serious chronic health effects, and potentially even a reduced life span from long-term exposure to wildland fire smoke (Navarro et al., 2019; Booze et al., 2004).

Because most wildland firefighters are deployed to both wildfires and prescribed fires during their career, an interesting question arises: are wildland firefighters exposed to more smoke, or more hazardous smoke at wildfires or prescribed fires? This section will address this issue and discuss management implications.

### 7.2.1 Health Hazards of Exposure to Smoke

Wildland fuels are composed of living and dead vegetation, and the burning of this fuel produces smoke. In a complete combustion environment, fuels are consumed by fire and converted mostly to carbon dioxide ($CO_2$) and water vapor ($H_2O$) with the release of heat. However, the combustion process in wildland fires is never complete, and incomplete combustion produces dozens of chemicals and hundreds of trace chemicals [Naeher et al. (2007); Reinhardt et al. (2000); Reinhardt and Ottmar (2000); Sandberg and Dost (1990); see CHAPTER 4 and CHAPTER 5]. Some of the combustion products may present acute health hazards, others may present chronic health hazards, and some can be both. The main inhalation hazards for wildland firefighters and other personnel at fire camp are carbon monoxide (CO) and respiratory irritants such as particulate matter (PM) and several key gases: acrolein, formaldehyde, and to a lesser extent nitrogen dioxide ($NO_2$) and sulfur dioxide ($SO_2$). Smoke also includes low concentrations of many other potentially toxic, carcinogenic components such as polycyclic aromatic hydrocarbons (PAHs), and although there is extensive scientific evidence indicating a relationship between long-term exposure to ambient fine particulate matter ($PM_{2.5}$; particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm)and lung cancer, the cancer risk of $PM_{2.5}$ derived from wildland fires remains unclear (U.S. EPA, 2019). Evidence to date indicates a PM occupational exposure limit is likely to be lower than the Occupational Safety and Health Administration (OSHA) standard for respirable nuisance dust (Kim et al., 2018). In addition to PM, wildland firefighters must also be protected against exposure to airborne soil dust, which can result in hazardous exposures to respirable crystalline silica.

### 7.2.2 Smoke Exposure at U.S. Prescribed Fires versus Wildfires

A relatively small number of studies have examined acute health effects to firefighters from smoke exposure during prescribed fire and wildfires across individual work shifts and entire fire seasons.

Although these studies indicate declines in individual lung function, a general conclusion from these studies is that smoke exposure does not exceed occupational exposure standards most of the time for both fire types (Adetona et al., 2016; Reinhardt et al., 2000; Reinhardt and Ottmar, 2000). However, when there is an exceedance, it is often related to the job assignment and duration of that assignment rather than the type of fire. For example, it has been shown that direct attack, line holding, and extensive mop-up can lead to high smoke exposures (Domitrovich et al., 2017; Reinhardt and Ottmar, 2004; Reinhardt et al., 2000; Reinhardt and Ottmar, 2000). The job assigned to a wildland firefighter and the length of time the individual is carrying out that task will often be the overriding determinant of exceeding occupational exposure limits rather than the fire type.

Most of these studies however, only collected data from individuals during their work shift and did not consider smoke exposures outside their work period, allowing for a potential misinterpretation of the results. Ongoing research by National Institute for Occupational Safety and Health (NIOSH) is looking into wildland firefighter smoke exposure effects beyond their work shift, considering exposure during their off hours during a work assignment and extending the assessment of health effects to a season and career worth of smoke exposure attributable to wildland fire incidents.

#### 7.2.2.1 Daily Exposure

Wildland firefighter work shifts average approximately 12 hours with 7 hours on the fire line if assigned to a prescribed fire (Reinhardt et al., 2000). During the work shift, firefighters have the potential to be exposed to smoke concentrations that are similar to wildfires and the exposures will depend on job assignment and duration. However, the firefighter often will return to a clean air environment at their duty station until the next work shift begins, reducing the 24-hour average exposure level. In contrast, firefighters assigned to long-duration project wildfires average 14-hour work shifts with 10 hours on the fire line (Reinhardt and Ottmar, 2000). The increase in total work shift hours and longer assignments on the fire line increase the duration of exposure to smoke as compared to prescribed fires. An additional concern is the potential for continued exposure after a firefighter returns to a dusty, smoke-filled fire camp following their work shift, if poorly-sited fire camps are affected by smoke and inversion conditions, increasing the 24-hour exposure. For example, if the Air Quality Index (AQI) during off-duty exceeds 100 (i.e., orange: unhealthy for sensitive groups) due to PM in the fire camp, this can result in firefighters experiencing continuous exposure to high PM concentrations. As a result, the constant exposure to higher PM concentrations could result in greater long-term health consequences when compared to the same individual deployed to a prescribed fire where the duration and concentration of exposure is less. This could have greater long-term health consequences when compared to the same individual deployed to a prescribed fire.

#### 7.2.2.2 Career Exposure

Exposure to smoke over the career of an individual will depend on the number and duration of assignments to both wildfire and prescribed fire incidents. Type 1 crews (generally with the most experience, leadership, and availability) will generally be exposed to the most smoke because their primary job is firefighting, and the majority of their work shifts will occur on both wildfires and prescribed fires. Type 2 and type 3 fire crews (generally with less experience, leadership, and availability than type 1 crews) are believed to have fewer overall wildfire and prescribed fire assignments resulting in less overall exposure throughout their career (Navarro et al., 2019). Exposure limits to prevent chronic health effects from career-long exposure patterns have yet to be established for PM exposure from wildfire smoke.

### 7.2.3 Management Implications

Evidence confirms that wildland firefighters are exposed to a variety of pollutants and respirable crystalline silica at levels that can exceed recommended exposure limits during deployment at both wildfires and prescribed fires. It is common for short-term exposure (usually 15 minutes, where irritation, chronic or irreversible tissue damage does not occur) or maximum exposure limits to be exceeded during brief but intense exposures to smoke at both fire types (Henn et al., 2019). This is often related to job assignment and other associated factors such as the site fuel model, wind orientation (downwind being higher), crew type, relative humidity, type of attack, and wind speed. The resulting acute or short-term effects such as eye or respiratory irritation require management intervention to reduce the exposure. Recent National Wildfire Coordinating Group guidance on smoke exposure during wildland firefighting recommended a reduction in the acceptable exposure limit on a shift-average basis, and this may be adjusted further as ongoing research is completed.

Smoke exposure, whether due to a prescribed fire or wildfire is both a health and safety issue for firefighters, prescribed fire training classes, and annual refresher courses. A range of literature is available to better understand the potential acute and chronic effects that may result from exceeding smoke exposure limits, and how best to manage, limit exposure, and inform crew personnel (Sharkey, 1997).

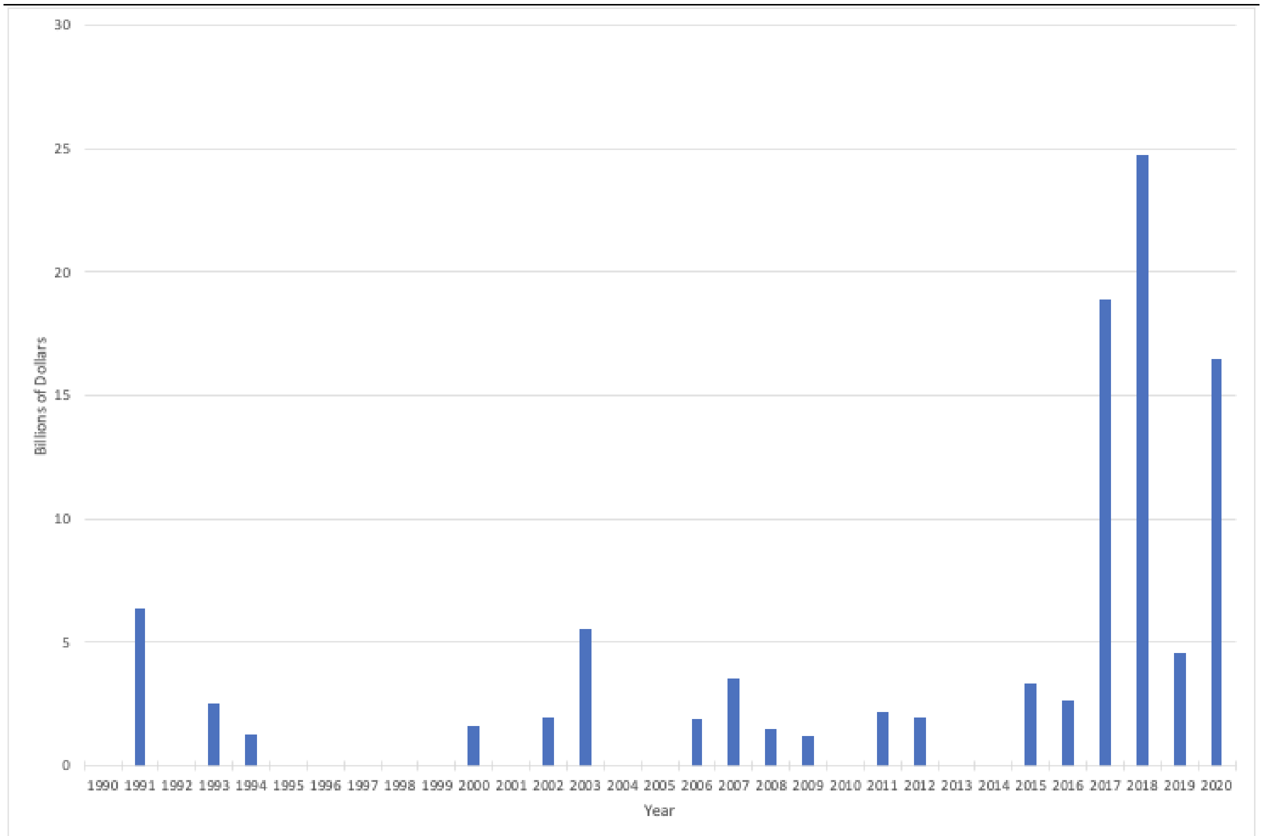
## 7.3 Economic Burden of Wildfire

NIST Special Publication 1215 (Thomas et al., 2017) quantified the burden on the U.S. economy from wildfires. The economic burden includes wildfire induced damages and losses, and also the management costs to suppress and mitigate ignition and fire spread (see Table 7-1). The annualized burden was estimated to be between $71.1 billion to $347.8 billion in 2016 dollars ($77.4 billion to $378.7 billion in 2020 dollars). The estimates were based on literature or data available in early- to mid-2017. Not included, for example, were recent catastrophic wildfire incidents. [Note, however, the estimates in Thomas et al. (2017) were significantly larger than the previous estimates found in NIST Special Publication 1130 Hamins et al. (2012)].

Based on NOAA billion-dollar weather and climate disaster data (Smith, 2020), which include direct losses from insured and uninsured sources, since 1980 the largest losses from billion-dollar wildfire disasters have all come since 2017 (Figure 7-1, note: there were no billion-dollar events prior to 1991). Since 1980, no year experienced more than a single billion-dollar wildfire disaster (direct losses from a single-event), meaning each year represents a single event in Figure 7-1. Accounting for more than just direct losses, Wang et al. (2020) measured the impacts from the 17 largest wildfires in California during 2018 and estimated their direct, indirect, and health costs. They estimated the wildfires to have caused $148.5 billion ($126.1 billion to $192.9 billion 95% confidence interval) in losses associated with direct capital losses ($27.7 billion), health effects ($32.2 billion), and indirect economic effects [$88.6 billion; Wang et al. (2020)].

## Table 7-1 The economic burden of wildland fires.

| Costs | Losses |
|---|---|
| **Prevention** | **Direct** |
| • Education and training | • Deaths and injuries |
| • Detection | • Psychological impacts |
| • Enforcement | • Structure and infrastructure loss |
| • Equipment | • Environmental impact |
| **Mitigation** | • Habitat and wildlife loss |
| • Fuels management | • Timber loss |
| • Insurance | • Agricultural loss |
| • Disaster resilience | **Indirect** |
| **Suppression** | • General economic impacts |
| • Federal | • Evacuation costs |
| • State | • Accelerated economic decline |
| • Municipal (paid) | • Utility and pipeline interruption |
| • Rural (volunteer) | • Transportation interruption |
| **Cross-cutting** | • Government service interruption |
| • Legal | • Psychological impacts (loss of amenities) |
| • R&D | • Housing market impact |
| • Building codes and standards | • Loss of ecosystem service |
| • Regulations | • Increase risk of other hazards |
| | • Loss of tax base |
| | • Health impacts from fire retardant use |




Source: Smith (2020), copyright permission pending.

**Figure 7-1 Billion-dollar wildfire event losses (1980−2020).**

It appears the economic burden from wildfire has been increasing over time. While the wildfires of the last few years have been particularly devastating, the increasing ability in measurement science to better account for wildfire impacts can also partly explain the increase in reported costs and losses. In particular is the recognition of human-health impacts from wildfire smoke as economic loss that has been underappreciated until recently.

The next section discusses economic issues related to wildfire management, followed by a section on management costs, and then a section covering economic issues related to valuing wildfire net value change (NVC).

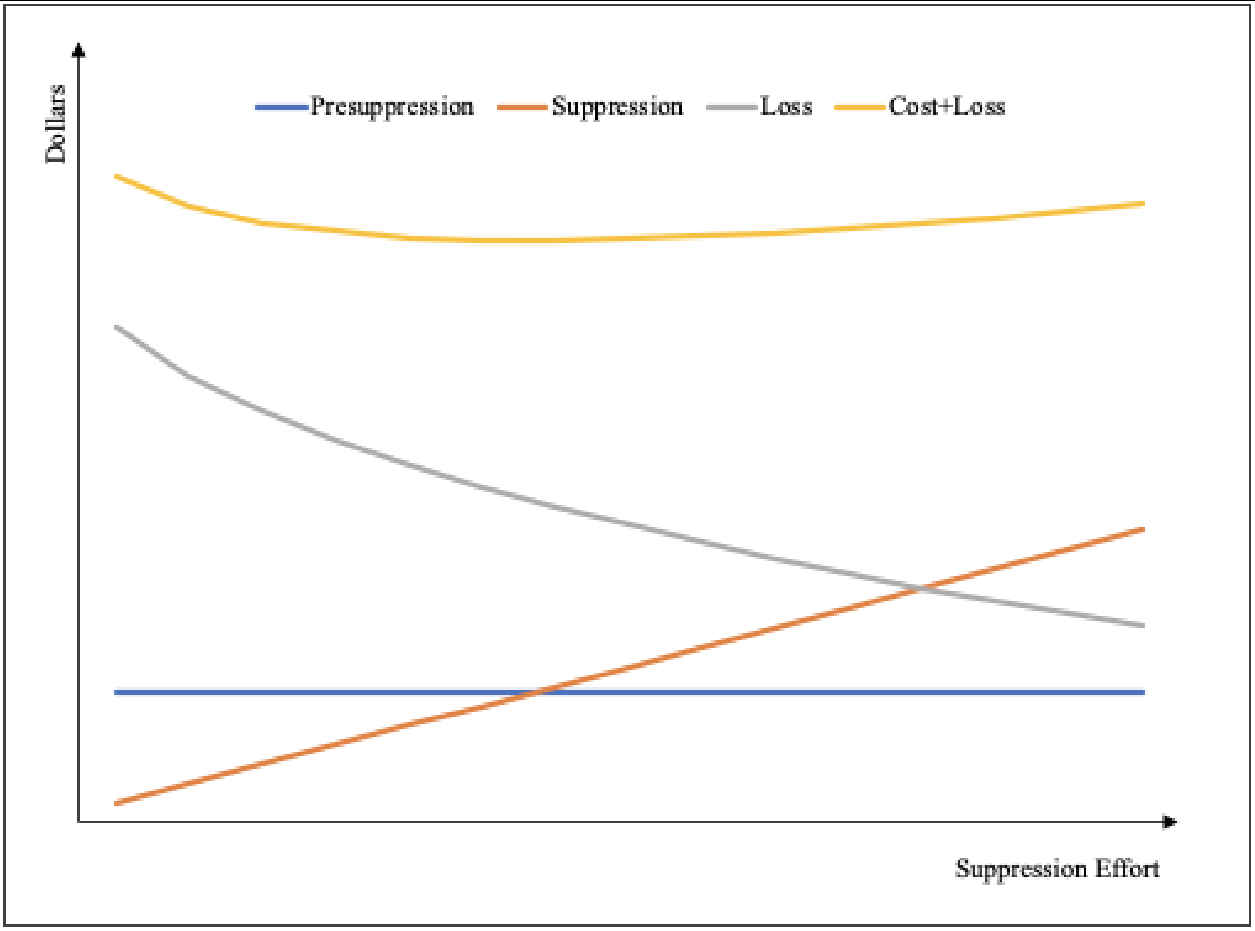
### 7.3.1 Economics of Wildfire: Management Implications

Economics is a discipline concerned with the allocation of scare resources and the understanding of trade-offs. Central to the economics of wildfire management is the search for the understanding of trade-offs between management inputs (e.g., prevention and suppression) and the consequences of unwanted wildfire ignitions (e.g., life-safety, acres burned, structure loss). The economics of wildfire management is not a new concept. In 1916, Headley (1916) discussed ideas of suppression effectiveness, efficiency, and waste of effort. Sparhawk (1925) introduced the idea of the "Cost plus Loss" (C+L) model as the management trade-off between prevention and prefire suppression expenditures, suppression expenditures, and wildfire losses. A central finding of the C+L model is that prevention and prefire suppression expenditures can be selected to minimize the sum of all costs (i.e., prevention, prefire suppression, and suppression spending) plus the resulting wildfire losses to identify the optimal level of management effort. The optimal level corresponds with the C+L minimum and it can be shown that at the minimum, any other allocation of management resources will either result in (1) an increase in spending that exceeds the expected avoided loss or (2) a reduction in spending that surpasses an increase in expected loss. This concept of the C+L model is depicted in C+L = cost plus loss.

Figure 7-2, where the inputs of presuppression and suppression are independent inputs, and presuppression expenditures are held constant (Donovan and Rideout, 2003; Sparhawk, 1925).

The C+L model has been revised several times [e.g., Gorte (2013); Gorte and Gorte (1979)], with modern depictions acknowledging the potential for positive impacts of wildfires, necessitating a change in the term "loss" to NVC; (Rideout and Omi, 1990; Simard, 1976). While the graphical depiction of the C+NVC is useful for illustration, it is less useful for identifying the minimum C+NVC when presuppression expenditures are allowed to be unconstrained. Further, because management activities and recent wildfire activity can have lasting impacts on the fuels, affecting future wildfire risk (Prestemon et al., 2002), intertemporal optimization is required. Intertemporal optimization introduces additional considerations such as discounting and risk perception, which affect the optimal timing of forest management activities (Mercer et al., 2007; Amacher et al., 2005a, b).

Two immediate challenges exist that make the identification of the optimal levels of intervention difficult to determine. First, an understanding of the functional relationship between wildfire management activities and the resulting NVC is needed. Second, and perhaps more fundamental, is that many of the impacts from wildfire are not well known or measured, particularly indirect or cascading impacts. However, additional challenges include (1) the costs and losses are not incurred by the same subsets of the population, creating equity concerns and barriers to aligning economic interests and (2) the spatial, temporal, and economic boundaries of the C+L loss model are hard to define.




C+L = cost plus loss.

**Figure 7-2 Illustrative example of the Cost plus Loss (C+L) Model of wildfire management.**

### 7.3.2 Management Cost Categories

Management cost categories include those expenditures spent on preparing for, mitigating, suppressing, and recovering from wildfires. Presuppression activities include prevention and preparedness. Suppression accounts for firefighter labor, equipment, firefighter training and wellness programs, as well as the monetary equivalence of volunteer time from local, nonpaid fire departments. Post-fire rehabilitation and recovery includes efforts to return lands to prefire functionality. The “cross-cutting” cost category includes activities that impact multiple management activities: for example, research and development efforts result in more effective suppression technologies, improved building codes, and fire-resistant building products.

#### 7.3.2.1 Preparedness and Prevention

At the federal level, prevention and mitigation activities, including wildfire detection and education, are aggregated together in budget line items as "preparedness." Preparedness is considered to be "comprise[d] [of] a range of tasks to ensure readiness for wildfire response, including workforce preparation, equipment and resource management, and wildfire outlook conditions for forecasting" (Hoover, 2020). For FY2020, preparedness spending was $1.672 billion dollars in total for the U.S. Forest Service (80%) and the Department of Interior [20%; Hoover (2020)].

Wildfire prevention activities include awareness efforts to promote fire safety to reduce unintentional wildfire ignitions. Awareness programs, such as public service announcements and media spots, community townhall-style presentations by wildfire prevention specialists, distribution of brochures and flyers containing educational messaging, and community wildfire hazard assessment performed by risk specialists have all been shown to reduce the numbers of human-caused unintentional wildfire starts and generate positive economic return on investment (Prestemon et al., 2010). For example, Prestemon et al. (2010) estimated that the benefit-cost ratio of prevention to be 35 to 1 on the margin. Abt et al. (2015), who also accounted for law enforcement efforts and intentionally-set wildfires, found benefits were 5 to 38 times larger than prevention costs. Prevention efforts have been shown to have differential effects that vary by ignition cause type [e.g., escaped campfire, debris fire; Butry and Prestemon (2019); Abt et al. (2015)] and the timing of activities can be exploited to yield larger economic benefits (Butry et al., 2010b; Butry et al., 2010a) or coupled with other risk reduction activities, such as fuels management (Butry et al., 2010b).

Early wildfire warning and detection systems, including aerial and satellite technologies, can lead to improved firefighting response time, limiting fire growth after ignition or assist in monitoring wildfire progression, and increase suppression effectiveness (Cardil et al., 2019). Satellite-based wildfire detection information has been shown to improve fire commanders' decision making during suppression activities, yielding better firefighting safety and economic outcomes (Herr et al., 2020). Steele and Stier (1998) found that wildfire surveillance from fixed lookouts yielded benefit-cost ratios of 6 to 1 in terms of reduced suppression costs and property losses.

Wildfire risk assessments and related tools can be used to identify occurrences of elevated temporal or spatial (landscape-level) risks, by factors such as prior wildfire history, weather, climate, fuel conditions, and other socioeconomic factors. Such information can be used to inform decisions on the prepositioning of mitigation and suppression resources (Bayham et al., 2020; Thomas et al., 2011; Prestemon and Butry, 2005). Improved suppression response time can yield economic benefits by reducing burned areas (Cardil et al., 2019).

### 7.3.2.2 Mitigation

Mitigation activities are designed to reduce the consequences from wildfire (e.g., area burned, value of economic loss). For wildfires, the primary mitigation approaches are fuels management, insurance, and disaster assistance.

#### 7.3.2.2.1 Fuels Management

Fuels management activities result in the reduction of hazardous fuels in forests. The reduction of fuels can be accomplished by a number of methods, including prescribed burning and mechanical and chemical thinning of materials (as discussed in CHAPTER 3). In FY2020, the federal government spent $194.0 million on the line item “hazardous fuels/fuels management” on federal lands and the line item “other Forest Service (FS) wildfire appropriations,” which also includes fuels management that amounted to $545.3 million (Hoover, 2020). Fuels management spending is not readily available at the state, local, and private levels, nationally.

There is statistical evidence that fuel treatments can impact wildfire behavior (Mercer et al., 2007; Prestemon et al., 2002), resulting in suppression cost savings in excess of treatment costs (Thompson et al., 2017; Taylor et al., 2013; Butry, 2009). Research into optimization has shown that with careful planning, fuel treatments can be leveraged to yield larger economics returns, when considering timing (Butry et al., 2010a) or when allowing for the sale of harvested materials after forest thinning (Prestemon et al., 2012). Beyond avoided suppression costs, Huang et al. (2013) identified additional benefits, including fatalities avoided, timber loss avoided, regional economic impacts, rehabilitation costs avoided, and carbon storage implications. In addition, Houtman et al. (2013) considered the impact of “free” fuel treatments (i.e., wildfire that are allowed to continue to burn to achieve multiple objectives which can include resource benefits) on future suppression costs avoided and found instances of large economic returns. However, policies allowing for more wildfires to burn (wildland fire use) may be more economically favorable with a low or zero discount rate. Furthermore, wildland fire use is controversial and carries inherent risk. Current federal fire management policy, for example, allows for limited wildland fire use (i.e., as long as the managers determine that it would not endanger the public). To increase the amount of wildland fire use, the risk thresholds would need to be relaxed, potentially resulting in more unintended losses of people, structures, and resources [see Houtman (2011)].

Fuel modification also occurs on private land, often as part of a program to create an area around a structure designed to reduce wildfire ignition and spread (i.e., “defensible space”). The major barriers to use of defensible-space programs are related to cost, aesthetics, and privacy (Absher et al., 2013; Kyle et al., 2010; Absher et al., 2009). For some, climate change and risk perceptions have mediated some of the resistance (Wolters et al., 2017), while for others it is a familiarity with the programs and expectations of its effectiveness that have led to acceptance. Stockmann et al. (2010) evaluated the cost-effectiveness of various homeowner risk reduction strategies including fuels management and structure hardening. They found that fuel reduction within 61 m (200 ft) of the house was the most cost-effective. Nevertheless, homeowner actions to reduce wildfire risk are potentially limited by the homeowners' own inaccurate assessment of risk factors [e.g., Champ et al. (2009)].

##### 7.3.2.2.2 Insurance

In measuring the U.S. fire problem, the cost of insurance has typically been calculated as the difference between premiums paid in and claims paid out (Hall, 2014), which constitutes overhead costs. These costs would include employees' wages, underwriting expenses, administrative expenses, taxes, real-estate expenses, legal expenses, and cost of capital. There are a number of insurance markets that are exposed to wildland fire, including homeowner's insurance, commercial insurance, automobile insurance (Hall, 2014), health and life insurance. Frequently, wildfire losses are reported as direct, insured losses.

Although insurance could be part of the solution to increased efforts to reduce overall risk to wildland fire on private lands, very few firms offer insurance focused in particular on forests (Chen et al., 2014). A leading limiting factor to widespread adoption of such insurance is a lack of actuarial information on wildfire risk at fine spatiotemporal scales. There is additionally a need to develop a better understanding of the approaches for reducing moral hazard and adverse selection in the issuance of policies. As a result, policies tend to be expensive and out of reach of small forestland owners, meaning that an insurance-based incentive structure for reducing overall wildfire risks on private lands remains elusive.

##### 7.3.2.2.3 Disaster Assistance

Disaster assistance is financial assistance provided by the federal government following a disaster declaration. Because assistance can be used for things such as temporary housing, lodging expenses, repair, replacement, housing construction, child-care, medical expenses, household items, clean-up, fuel, vehicles, moving expenses, and other necessary expenses determined by the Federal Emergency Management Agency (FEMA), care needs to be taken in tracking the economic burden of wildfires because counting these costs or reimbursements directly and also as disaster assistance may result in double counting.

#### 7.3.2.3 Suppression

In FY2020, at the federal level, suppression spending exceeded $1.4 billion dollars, split between the U.S. Forest Service (73%) and the Department of Interior [27%; Hoover (2020)]. State suppression expenditures are estimated at $1 billion to $2 billion a year (Gorte, 2013).

An estimate for local (municipal) fire departments is more difficult to determine. An approximation can be calculated assuming the cost of wildfire prevention and suppression is proportional to the incident volume of fire involving wildland fuels. In 2014, based on Zhuang et al. (2017), it is estimated that career fire department expenditures amounted to $41.9 billion ($46.21 billion in 2020 dollars), and the value of volunteer (rural) fire departments is estimated at $46.9 billion [see "method 5" used in Zhuang et al. (2017); $51.72 billion]. Based on reported call volume (27.8 million calls) reported to the National Fire Incident Reporting System (NFIRS) data from 2018, fires involving natural vegetation represented 0.8% of all calls (20% of all fire incidents). In combination with fire department expenditures, this information could be used to estimate the amount spent to suppress wildland fires in local jurisdictions.

Gebert et al. (2007) found suppression spending to be impacted by burned area, suppression strategy, and region of the country. Statistical models developed to forecast U.S. Forest Service suppression costs by region of the country show that forecasted suppression spending is influenced by factors such as prior suppression expenditures, sea surface temperatures, and weather [e.g., temperature and precipitation; Gebert and Black (2012); Abt et al. (2009)] found that suppression strategy influences total suppression costs for large wildfires, with direct suppression being the most expensive on a per acre burned and per day basis but leads to smaller wildfire sizes and duration. However, studies have found that overall suppression strategy can be complicated by other factors, which also impact total suppression expenditures. For example, Liang et al. (2008) found that the percentage of private land within the burned area influenced suppression expenditures on large wildfires, while Rossi and Kuusela (2020) indicated that management risk attitudes (risk aversion) impact expenditures.

#### 7.3.2.4 Post-Fire Rehabilitation and Recovery

Post-fire rehabilitation is funded at the federal level as part of "other activities," and in FY2020 the other activities amounted to $41.9 million. Also included in this line item are activities related to research and development, construction and maintenance of fire facilities, and forest health management (Hoover, 2020).

#### 7.3.2.5 Cross-Cutting Cost Categories

There are several costs that cut across various organizations and categories. These include legal costs, research, and regulations. Legal costs include the prosecution, defense, and incarceration of fire-setters. In 2019, there were 785,500 prisoners in local prisons (Zeng and Minton, 2021). In 2019, there were 1,430,805 prisoners in federal and state facilities, with 0.9% sentenced for "other" property crimes, which include arson [all types; Carson (2020)]. The Bureau of Prisons (2018) estimated that the average cost of incarceration for a federal inmate in fiscal year 2016 was $36,299.25 ($39,566.18 in 2020 dollars).

Many public and nonprofit organizations are involved in research and development to reduce the costs and losses associated with wildland fires. For federal research and science agencies, some of these costs are included in the $41.9 million "other activities" listed above (Hoover, 2020).

Each state has its own building codes and fire regulations, based on the international model codes. In addition, some consumer products are built for fire safety. Zhuang et al. (2017) estimated in 2014 that fire-safety related costs for building construction were $57.4 billion ($63.30 billion in 2020 dollars) and for consumer products were $54.0 billion ($59.55 billion in 2020 dollars). This includes fire safety from all ignition and risk sources. In a study comparing the construction costs of a typical house with a "wildfire-resistant" house, Quarles and Pohl (2018) found that the costs components to total slightly less expensive for the wildfire-resistant house ($79,230 vs. $81,140). The cost components included the roof, exterior walls, deck, and landscaping. The largest savings were found for the exterior walls, which more than offset increases to the other components.

### 7.3.3 Wildfire Loss Categories

Wildfire-induced losses are grouped into two categories: direct and indirect. Direct losses are those that occur as a primary result of wildfire (e.g., structure loss), while indirect losses are those that occur as a secondary, or cascading, result of wildfire (e.g., economic downturn due to business structure loss). Indirect losses are often more difficult to quantify due to latency and many may only be realized years after the wildfire.

#### 7.3.3.1 Direct Losses

##### 7.3.3.1.1 Fatalities and Injuries

The National Fire Protection Association (NFPA) reported 80 civilian (nonfire-service) fatalities and 700 injuries in 2019 from fire incidents reported as "outside and other fires" (Ahrens and Evarts, 2020). The "outside and other fire" incident type includes wildland, grass, crop, timber, and rubbish fires. The estimates are based on a survey to U.S. fire departments, meaning the fatalities and injuries would tend to include those observed or reported immediately following the fire incident. Long term health consequences made worse due to fire exposure, but not known until well after the incident, would not be captured. In 2017, there were 10 firefighter deaths associated with wildland suppression activities (USFA, 2018). The Incident Management Situation Report system, which tracks data on wildfires in federal jurisdictions, includes firefighter injuries. From 2003 to 2007, an average of 260 injuries per year were reported (Britton, 2010).

#### 7.3.3.1.2 Psychological Impacts

Studies from wildfires have found depression, post-traumatic stress disorder (PTSD), and other anxiety disorders to have resulted from exposure to wildfire events. Estimates for civilian rates of PTSD and other anxiety disorders after a disaster range from 30% (Cole, 2011) to 60% (Kuligowski, 2017), with effects sometimes taking years to manifest (Kuligowski, 2017). For first responders, rates of PTSD have been estimated to occur in up to 20% of firefighters and paramedics (Rahman, 2016).

#### 7.3.3.1.3 Structure and Infrastructure Loss

The National Interagency Coordination Center (NICC) reported 963 structures lost by wildfire in 2019, under the annual average of 2,593 (NICC, 2019). NICC reported 25,790 structures lost in 2018 (NICC, 2018) and 12,306 structures lost in 2017 (NICC, 2017). NICC does not provide dollar lost estimates.

#### 7.3.3.1.4 Environmental Impacts

Environmental impacts can take many forms, including impacts on vegetation, soil and erosion, watershed, and carbon sequestration. Vegetation loss can create the need to reseed and regrow forest and grasslands. Soil degradation can result in poor soil nutrients and vegetation growth. Both vegetation and soil loss can result in erosion and increase the risk of mudslides (Ren et al., 2011; Benda et al., 2003). Trees sequester carbon, but it can be released to the atmosphere if trees are burned. Wildfires can decrease water quality through the introduction of carbon, metals, other containments, and changes to nutrients, which can affect aquatic ecosystems and drinking water (Rhoades et al., 2019b). In addition to increased treatment costs for potable water, poor water quality can impact agricultural and industrial operations (Bladon et al., 2014). Treatment costs include the increased need for elimination of solids and dissolved organic carbon in water impacted by discharge from burned forests and wildlands (Emelko et al., 2011). However, traditional water quality protection strategies would fail to recognize impacts, requiring treatment, from wildfire (Emelko et al., 2011)).

#### 7.3.3.1.5 Timber and Agricultural Loss

Wildfires on lands managed for timber and agricultural purpose result in business losses. The 1998 Florida wildfires resulted in pine timber damage of between $300 to $ 500 million in 1998 dollars

($479 million to $798 million), which represented over half of the quantified costs and losses of the wildfire event (Butry et al., 2001). The timber losses were from two effects: (1) value from the physical loss of timber and (2) a price increase, due to scarcity, after all salvageable timber was sold. Prestemon et al. (2006) evaluated salvage harvest scenarios following the 2000 Bitterroot wildfire and found similar (direction of) impacts to consumers, owners of damaged stands, and owners of undamaged stands. They demonstrate that the value of timber lost due to wildfire could be more than offset (in general welfare effects) through salvage.

### 7.3.3.2 Indirect Losses

#### 7.3.3.2.1 General Economic Impacts

Wildfires, and disasters in general, can have long lasting impacts on an economy. They can include business interruption (temporary and permanent closures) and supply chain impacts. Supply chain disruption can affect businesses and customers far removed from the wildfire threatened areas.

Butry et al. (2001) found the 1998 Florida wildfires impacted the tourism and service sectors. In an analysis of the 2002 Haymen Fire [Colorado; Kent et al. (2003)] found the wildfire induced overall employment growth of 0.5%, by creating shifts in the economy resulting in a decline in average wages by 3%. Focusing on employment and wage dynamics, Davis et al. (2014) examined the impact of the 2008 large wildfires in Trinity County, California. They found that employment in the natural resource sector increased by 30%, while average wages fell by 19%; whereas wage growth was experienced in the other sectors, again demonstrating disparate effects. Borgschulte et al. (In Press) found that wildfire smoke impacts annual labor income and employment in the U.S. and estimates the economic loss to be four times that from mortality ($83 billion in 2020 dollars).

Nielsen-Pincus et al. (2014) explored the economic impacts of large wildfires (fires where suppression exceed $1.0 million) in the western U.S. states by economic sector. For counties with populations under 250,000, they found sectors with employment increases included natural resources and mining; trade, transportation, and utilities; information services; financial services; and federal employment. Sectors that lost employment included construction, manufacturing, professional and business services, education and health services, and leisure and hospitality services. For larger counties, total employment was reduced after a large wildfire by 0.04%.

Loomis et al. (2001) found in a study of visitors to forests in Colorado that hikers and mountain bikers responded with fewer visits in areas with crown fires, but the time since the fire also played a role. Englin et al. (2008) and Englin et al. (2001) found the linkage to recreation demand is time dependent, with recent wildfires correlated with increased visitation and older wildfires linked to fewer, with Englin et al. (2001) also noting a rebound effect with the oldest wildfires. Hesseln et al. (2003) found crown and prescribed fires reduced visitation, visitation to the recovery area, but consumer surplus differed between hikers (increased) and mountain bikers (decreased) in New Mexico. In Montana, Hesseln et al. (2004) found hikers decreased visitations due to crown fire, but increased visitations due to prescribed fire. They found mountain bikers displayed the opposite pattern.

#### 7.3.3.2.2 Evacuations

Evacuation costs include temporary lodging and travel to and from the impacted area. Kent et al. (2003) found the Hayman Fire in Colorado resulted in other expenditures, which included evacuation, that were estimated to be up to $14 million ($19.5 million in 2020 dollars). In addition to expenditures, McCaffrey et al. (2015) mentioned the nonmonetary expenditures, including the "logistical" and "emotional" toll of fire evacuation.

#### 7.3.3.2.3 Lost Natural Amenities

National forests provide a stream of values including historic, use and recreational, and existence (value someone places on knowing something exists whether or not they may ever visit or use). Some of these values can be monetized in the form of entrance and use fees. The National Parks were estimated to be worth $92 billion dollars [$100 billion in 2020 dollars; Haefele et al. (2016)].

#### 7.3.3.2.4 Housing Market

Hedonic analyses that relate home sales prices to nonmarket amenities and other property attributes can detect the values of environmental goods and services not directly traded in markets. Several studies have evaluated the effect of wildfire risk on home sales prices, with the expectation that higher risk lowers sales prices, all else being equal. Loomis (2004) compared housing sale prices before and after the 1996 Buffalo Creek Fire (Colorado) and found a price decline between 13 to 15% of undamaged homes near the wildfire. Kim and Wells (2005), in a study of the greater Flagstaff area (Arizona), found moderate crown canopy closure (40 to 69%) was shown as preferred by home buyers; whereas high crown canopy closure (70% and higher), which posed a higher wildfire risk, was shown to decrease sale prices.

Meldrum et al. (2015) explored whether wildfire risk perceptions of residents of homes in Ouray County, in southwestern Colorado, aligned with professionals' data-based assessments of wildfire risk based on features of the home and property, including whether the property had vegetation nearby. Residents underestimated the risks of wildfire nearby. In many other aspects of the property's features, residents' perceptions were generally not highly correlated with the assessments of the professionals. The implication is that economic motivations to undertake risk reduction efforts would be lower than if risk were more accurately quantified by residents. Donovan et al. (2007) compared housing sales prices before and after homes were rated based on wildfire risk in Colorado Springs, CO. They found that the availability of risk information was correlated with a decrease of a representative home sales value by 13.7%. Champ et al. (2009) explored whether home prices in Colorado Springs, CO were aligned with risks of wildfire. They found that homebuyers prefer risky locations due to their favorable amenities besides fire (e.g., topography) but that homebuyers were less cognizant of wildfire risks than objective assessments would identify. Although these homebuyers preferred less fire-prone building materials, they tended to undervalue features of their properties from the perspective of wildfire risk reduction.

Hjerpe et al. (2016), in a study of house prices in four western cities, found that the sales of homes with medium forest density (34 to 66%) within 100 m of a house was associated with lower sales prices; yet, homes with high forest density (67% and greater) within 500 m of a house was associated with higher sales prices. Stetler et al. (2010) estimated home sales prices in Montana and found that distance to the wildfire, time since, size of fire, and whether the home was within sight distance of the wildfire affected home sales, for an average price loss of −13.7% for a home within 5 km of the fire.

Kalhor et al. (2018) evaluated the impact of visible fire scars from the 2000 Cerro Grande fire (New Mexico) on assessed house values in 2013. They found impact of the previous damage equated to a 1.7 to 4.4% decline in assessed house value, while measures of future wildfire risk were found to be correlated to an increase in assessed house value by 0.3 to 0.4%. The latter impact was attributed to the crown area likely accounting for the aesthetic value of vegetation.

##### 7.3.3.2.5 Loss of Ecosystem Services

Ecosystem services are generally defined as “any positive benefit that wildlife or ecosystems provides to people” (NWF, 2017). Few studies exist on a national scale. Most tend to be regional in scope and not specific to wildfire. For example, Loomis et al. (2000) evaluated the value of better watershed services for a 45-mile section of the Platte River, Desvousges et al. (1983) valued lake preservation, Moore and McCarl (1987) valued the preservation of Mono Lake ecosystem, and Hanemann et al. (1991) valued increased salmon stock in the San Joaquin River. Such examples provide methods that could be used to value avoided losses to ecosystem services from wildfire mitigation.

### Wildfire Fire and Prescribed Fire Impacts on Forest Health and Wildlife

Studies in the ponderosa pine ecoregion of California, Oregon, and Washington have shown that fire management based on low-intensity prescribed fire coupled with mechanical thinning can, over time, approximate historical landscape conditions that are much less susceptible to catastrophic fires (Prichard et al., 2017a; Prichard et al., 2017b; Allen et al., 2002). Where it is feasible to use such practices, low-severity fires can promote important wildlife habitat and forest health benefits (Pausas and Keeley, 2019). These ecological benefits include improvements in habitat quality for threatened and endangered species (Pausas and Keeley, 2019); reductions in ground layer and understory “ladder” fuels; reduced losses of forest floor nutrient capital and water holding capacity (Murphy et al., 2006); and increased forest resistance to drought, pests and diseases, all of which are being exacerbated by climate change (Spies et al., 2019; Vose et al., 2019).

To date, prescribed low-intensity fire and thinning treatments have not been adopted into local, state, and federal forest management practices at a scale necessary to affect the overall fire deficit, and associated fuel load excess, in western forests. The potential impacts of ignoring the fire deficit is underscored by the growing body of evidence for the role of climate change in amplifying recent increases in the frequency and intensity of wildland fires (Kolden, 2019; Abatzoglou and Williams, 2016) and consequent impacts on ecological benefits associated with low-intensity fire regimes.

### Water Resources

Wildfire can both directly and indirectly affect water resources as well. Direct effects can occur via downwind smoke and ash deposition on the surface of waterbodies (see Section 6.4), and damage to drinking water infrastructure. Indirectly, fire affects water resources primarily through increased runoff of water and other materials into nearby waterbodies. Together, these direct and indirect effects can alter the physical, chemical, and biological characteristics of water resources, and by doing so, impact their end use, such as for recreation, aquatic life, and drinking water.

The direct effects of fire on drinking water infrastructure is an area of rising concern. Fires can damage water treatment facilities or water supply lines, for example. In two locations in California (Santa Rosa and Paradise), benzene and other volatile organic compounds (VOCs) were detected in tapwater post-fire, with concentrations of benzene exceeding federal and state drinking water standards (Proctor et al., 2020). This was likely caused by the partial melting of plastic water-supply lines to homes and infiltration of hot gas and other materials when the supply system became depressurized (Proctor et al., 2020). As fires become more frequent, they are increasingly likely to burn into urbanized areas, and direct effects on drinking water infrastructure could be become more common.

The indirect effects of fire are more widespread currently, including the indirect effects on waterbodies used as drinking water sources. Fire-prone ecosystems are major sources of the national water supply. Fire impacts on forested watersheds are particularly concerning as these watersheds provide 50% of the water consumed in the lower 48 states. Most of these watersheds are at high risk from wildfire now or in the near future (Hallema et al., 2018).

Fire can impact the physical supply and timing of water delivery by altering runoff and streamflow. The loss of ground layer vegetation and canopy leaf biomass reduces evapotranspiration, potentially resulting in pronounced increases in runoff and flood severity (Stevens, 2013). Moreover, on some soil types, intense wildfires can dramatically increase runoff by increasing water repellency of near-surface soil layers, a condition that can persist for years (Certini, 2005). Depending on fire severity, rainfall patterns, and watershed soil and land cover characteristics, post-fire streamflow can increase in the days, months and years following fire (Niemeyer et al., 2020). Fire can also change the amount and timing of snowmelt. For instance, mountain snowpack beneath charred forests absorbed more solar energy, causing earlier melt and snow disappearance in >11% of forests in the western seasonal snow zone over the past two decades (Gleason et al., 2019). Fire and climate change impacts on snowpack can also have significant impacts on late summer runoff when it is most needed by fish and wildlife (Pausas and Keeley, 2019).

By increasing runoff and flow, fires can also increase erosion and delivery of sediments, ash, and other constituents to downslope ecosystems. The increased sediment loads and land destabilization that can occur post-fire (Ren et al., 2011; Benda et al., 2003) may be characterized by a large influx of suspended solids to headwater streams, termed "slurry flows", up to 700,000 mg/L in magnitude (Rinne, 1996). A wide variety of chemical constituents are often mobilized along with the sediments and ash. This includes nutrients and cations, heavy metals, organic compounds, like polycyclic aromatic hydrocarbons (PAHs), and dissolved organic carbon (Smith et al., 2011). Besides direct additions to water resources, fire can indirectly increase disinfection byproducts (DBPs), compounds that form during drinking water treatment when disinfectants (e.g., chlorine, chloramine) react with organic carbon and nitrogen compounds present in higher concentrations post-fire (Bladon et al., 2014). Some DBPs pose health risks, with the potential to cause certain cancers, reproductive issues, and anemia.

Encroachment of wildfire into the wildland/urban interface can also release largely unknown types and quantities of anthropogenic contaminants into streams. Combustion of houses, buildings, vehicles, waste sites and other infrastructure present risks from hazardous chemicals, such as benzene and VOCs, as well as heavy metals (Proctor et al., 2020; Uzun et al., 2020). Finally, the use of fire retardants may also increase nutrient and chemical loading to post-fire landscapes.

Beyond physical and chemical changes, fires can also indirectly alter biological assemblages in downstream waters. Fire can increase coarse woody debris in streams (Young, 1994), positively impacting long-term habitat for fish, yet over the shorter term, fish and macroinvertebrate populations typically decline post-fire [e.g., Rinne (1996)]. Concomitantly, burning in riparian areas can increase light levels to streams, and studies have often recorded increases in stream temperatures post-fire [e.g., Dunham et al. (2007)]. This could negatively affect cold-water fish species, like salmonids (Beakes et al., 2014). Combined with the increased light and temperature, an influx of nutrients and sediment can also promote harmful algal blooms and the production of cyanotoxins (Bladon et al., 2014; Smith et al., 2011). These cyanotoxins both contaminate drinking water and negatively affect aquatic life.

While wildfire has been a part of the natural ecology of many ecosystems for millennia, the increase in fire frequency, intensity and area burned can have deleterious effects on water resources, altering their physical, chemical, and biological characteristics. In general, the more severe the fire, the more likely downstream waters will be affected. Water quality impacts generally are most pronounced in the first few years post-fire but may persist for more than a decade in some cases (Rhoades et al., 2019a;

Smith et al., 2011). Increased concentrations of nutrients, heavy metals, organic compounds like benzene, and DBPs pose particular risks, along with increased algal blooms and cyanotoxins. Communities will need to be aware—and plan for—the potential for post-fire contamination of water resources. The provisioning of safe drinking water from burned watersheds may require additional treatment infrastructure and increased operations and maintenance costs to remediate effects.

##### 7.3.3.2.6 Other

Other impacts of wildfires include accelerated economic decline, loss of utilities and transportation systems, disruption to government services, interference with military operations (e.g., smoke visibility issues), cascading natural hazard risks (e.g., increase risk of mudslide or growth of invasive species), loss of tax base due to housing and building stock, and health and environmental impacts from fire retardants. Many of these impacts are not well-defined or monetized.

### 7.3.4 Magnitudes, Gaps, and Uncertainty

Table 7-2 shows estimated magnitudes of value of the costs and losses and levels of uncertainty in their measurement or ability to measure at a national scale [reproduced from Thomas et al. (2017)]. The estimated magnitudes and uncertainties were based on the values found in the report, and where not available, were estimated using expert judgment of the report authors. The largest cost and loss categories were fuel treatments and defensible space, suppression, economic value of deaths and injuries, evacuation costs, and housing market impacts. The largest sources of uncertainty tended to be indirect economic effects, insurance, and some of the cross-cutting categories (e.g., building codes and standards, regulations).

While there exists a significant literature detailing components of the costs and losses associated with wildland fire, producing an annual national estimate, which could be tracked over time to evaluate management success, is difficult at this time without introducing large sources of uncertainty in the estimates. However, it does appear that the economic burden from wildland fire is increasing over time.

**Table 7-2 Magnitude and uncertainty associated with the economic burden of wildfire at the national level.**

| | Order of Magnitude | Uncertainty |
|---|---|---|
| **Costs** | | |
| **Preparedness** | $$$$ | ? |

**Table 7-2 (Continued): Magnitude and uncertainty associated with the economic burden of wildfire at the national level.**

| | Order of Magnitude | Uncertainty |
|---|---|---|
| **Mitigation** | | |
| Fuels management | | |
| Fuel treatments (Rx fire, thinning) | $$$ | ? |
| Defensible space/firewise | $$$$ | ??? |
| Insurance | $$ | ???? |
| Disaster assistance | $ | ?? |
| **Suppression** | | |
| Fire departments (labor, equipment, training) | | |
| Federal | $$$$ | ? |
| State | $$$$ | ? |
| Municipal (professional) | $$$$ | ??? |
| Rural (volunteer) | $$$$ | ??? |
| **Cross-cutting** | | |
| Legal | | |
| Prosecution | $$ | ?? |
| Incarceration | $$$ | ?? |
| Civil/liability | $$ | ???? |
| Science/research and development | $$ | ??? |
| Building codes and standards | $$ | ???? |
| Regulations (e.g., zoning) | $$ | ???? |
| **Losses** | | |
| **Direct** | | |
| Deaths and injuries (civilian and firefighter) | $$$$ | ?? |
| Psychological impacts (PTSD) | $$ | ??? |
| Structure and infrastructure loss | $$$ | ??? |

**Table 7-2 (Continued): Magnitude and uncertainty associated with the economic burden of wildfire at the national level.**

| | Order of Magnitude | Uncertainty |
|---|---|---|
| Environmental impact | $$$ | ???? |
| Habitat and wildlife loss | $$ | ???? |
| Timber loss | $$$$ | ??? |
| Agriculture loss | $$$ | ???? |
| Remediation/cleanup | $$ | ??? |
| **Indirect** | | |
| General Economic impacts (business interruption, tourism, supply chain) | $$$ | ???? |
| Evacuation costs | $$$$ | ??? |
| Accelerated economic decline of community | $$$ | ???? |
| Utility and pipeline interruption (electricity, gas, water, oil) | $$$ | ???? |
| Transportation interruption (e.g., roads and rail) | $$ | ???? |
| Government service interruption (including education) | $$ | ???? |
| Psychological impacts (loss of natural amenities) | $$ | ???? |
| Housing market impact (loss due to fire risk) | $$$$ | ??? |
| Loss of ecosystem services (e.g., watershed/water service) | $$$ | ???? |
| Increased risk of other hazards (e.g., mudslide, invasive species) | $$$ | ???? |
| Decrease in tax base (structure loss or decline in value of structure) | $$$ | ??? |
| Decrease in government services | $$$ | ???? |
| Health/environmental impacts from use of fire retardants/suppressants | $$$ | ???? |

PTSD = post-traumatic stress disorder; Rx = prescribed.

Note: Classification of “order of magnitude”: $ = <millions; $$ = 10s millions; $$$ = 100s millions; $$$$ = billions; “uncertainty”: ? = low; ?? = medium; ??? = high; ???? =unknown.

## 7.4 References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# CHAPTER 8 ESTIMATED PUBLIC HEALTH IMPACTS

## 8.1 Introduction

A main goal of this assessment is to provide a quantitative comparison of the estimated health impacts and associated economic values attributed to smoke from wildland fire (i.e., wildfire and prescribed fire) under different fire management strategies by focusing on two case study fires: Timber Crater 6 (TC6) and Rough fires. Previous chapters of this assessment describe in detail the air quality impacts of each case study fire and defined hypothetical scenarios meant to reflect different fire management strategies (CHAPTER 5) and the health effects of wildfire smoke (CHAPTER 6), which collectively represent key inputs to the process of quantitatively estimating health impacts. Within this chapter, the information presented in previous chapters is used to conduct analyses using U.S. Environmental Protection Agency's (U.S. EPA's) Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE) to provide additional insight on the overall public health impacts of wildland fire smoke and how those impacts can vary depending on the fire management strategy employed.

## 8.2 Benefits Mapping and Analysis Program—Community Edition (BenMAP–CE) Analysis

BenMAP–CE quantifies the number and economic value of air pollution-related premature deaths and illnesses (Sacks et al., 2018). The program draws upon a library of preinstalled and user-imported input parameters (Table 8-1) to systematize the procedure for calculating the estimated health impact and then valuing the resulting counts of adverse effects. The sections below describe the steps to configuring and running BenMAP–CE to estimate the number, and corresponding economic impact, of wildland fire-related particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm ($PM_{2.5}$) and ozone-attributable effects.

**Table 8-1 Key data inputs for Benefits Mapping and Analysis Program—Community Edition (BenMAP–CE) used to estimate health impacts for the case studies.**

| Data Input | Source |
|---|---|
| Air quality data | Modeled $PM_{2.5}$ and ozone concentrations from each case study[a] |
| Population counts | U.S. census data allocated to air quality model grid cells, stratified by race, sex, age, and ethnicity and projected to the Year 2021 |
| Risk coefficients | Concentration-response relationships from U.S-based air pollution epidemiologic studies examining $PM_{2.5}$, ozone, and wildfire-specific $PM_{2.5}$[b] |
| Baseline rates of death and disease | Centers for Disease Control and Prevention provided death rates, and Healthcare Cost and Utilization Program provided hospital visit rates for all other areas |

BenMAP–CE = Benefits Mapping and Analysis Program—Community Edition; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

[a]For more information see CHAPTER 5

[b]For more information on epidemiologic studies examining wildfire-specific $PM_{2.5}$ see CHAPTER 6

### 8.2.1 Health Impact Function

This analysis estimates the number of wildfire and prescribed fire-attributable premature deaths and illnesses associated with the TC6 and Rough fire case studies using a health impact function. The following example Equation 8-1) details the approach for calculating $PM_{2.5}$-attributable premature deaths; the approach for quantifying PM-attributable morbidity impacts and ozone-related mortality and morbidity impacts is identical except for the ages for which the function is calculated, as detailed below. Counts of $PM_{2.5}$-attributable total deaths ($y_{ij}$) are calculated for period $i$ ($i$ = 2021) among individuals of all ages (0−99) (a) in each county $j$ ($j = 1,\ldots,J$ where $J$ is the total number of counties) as:

$$y_{ij} = \sum a \, y_{ija}$$

$$y_{ija} = mo_{ija} \times (e^{\beta\, cij-1}) \times P_{ija,}$$

**Equation 8-1**

where $mo_{ija}$ is the daily baseline all-cause mortality rate for individuals aged $a$ = 0−99 in county $j$ in Year $i$ stratified in 10-year age groups, β is the risk coefficient for all-cause mortality for adults associated with $PM_{2.5}$ exposure, $C_{ij}$ is annual mean $PM_{2.5}$ concentration in county $j$ in Year $i$, and $P_{ija}$ is the number of residents aged $a$ = 0−99 in county $j$ in Year $i$ stratified into 5-year age groups. When calculating impacts, the program assigns the 10-year stratified death rate to the corresponding 5-year stratified population bin. The health impact function used to calculate all other impacts is identical to Equation 8-1, except for the effect coefficient. The program performs a Monte Carlo analysis by randomly sampling 5,000 times from a distribution constructed from the standard error reported for each study; the resulting distribution is then used to report 95% confidence intervals.

The function above is calculated using BenMAP–CE (v1.5.5.1), a tool that contains the baseline incidence rates, population counts, and health impact functions needed to quantify counts of $PM_{2.5}$ and ozone attributable deaths and respiratory hospital admissions (U.S. EPA, 2019; Sacks et al., 2018). This approach to quantifying air pollution health impacts, and the adverse effects of wildland fires in particular, has been used within the peer-reviewed literature (Fann et al., 2019; Fann et al., 2018; Berman et al., 2012). The following sections describe the specification of each input parameter within BenMAP-CE for the purposes of the analyses conducted within this assessment.

### 8.2.2 Air Quality Modeling

The emissions inputs and photochemical modeling simulations performed to predict the $PM_{2.5}$ and ozone concentrations attributable to each case study fire, prescribed fire activity in each location, and defined hypothetical scenarios are detailed in CHAPTER 5. As noted in 0, for each hypothetical scenario, wildfire specific air quality impacts (the delta used to estimate the change in health impacts) is calculated using a baseline of no case study fire to estimate the burden attributed to the actual fire, prescribed fires, and hypothetical scenarios for each case study. BenMAP–CE used the model-predicted daily mean $PM_{2.5}$ and model-predicted daily 8-hour max ozone concentration to quantify health impacts for the following actual fire and hypothetical scenarios for each case study:

<u>TC6 Case Study</u>

- Actual TC6 Fire
- Hypothetical Scenario 1 (small): a smaller hypothetical TC6 Fire in a heavily managed area (most prescribed fire/fire managed for resource benefits), which would equate to a wildfire with less fuel, a smaller fire perimeter, and less daily emissions
- Hypothetical Scenario 2a (large): a larger hypothetical TC6 Fire, but not the “worst-case” scenario, due to no land management which would equate to a wildfire with more fuel, a larger fire perimeter, and more daily emissions
- Hypothetical Scenario 2b (largest): a much larger, hypothetical “worst-case” scenario TC6 Fire with no land management (i.e., no prescribed fire/managed fire) which would equate to a wildfire with the most fuel, largest fire perimeter, and largest daily emissions
- Prescribed fires: three prescribed fires that occurred in the past and one prescribed fire that occurred in 2019, all modeled to occur on the same days in September 2019 that fit prescription conditions

Rough Fire Case Study

- Actual Rough Fire
- Hypothetical Scenario 1 (small): a small hypothetical Rough Fire that represents the combined impact of the proposed Boulder Creek Prescribed Fire and the Sheep Complex Fire, a wildfire managed for resource benefits, on reducing the overall size of the Rough Fire
- Hypothetical Scenario 2 (large): a large hypothetical Rough Fire that allows for the fire perimeter of the Rough Fire to progress into the area of the Sheep Complex Fire as if both the Boulder Creek Prescribed Fire and Sheep Complex Fire did not occur
- Boulder Creek Prescribed Fire: a proposed prescribed fire that was planned, but did not occur in the fall of 2014
- Sheep Complex Fire: a wildfire that occurred in 2010 due to a lightning strike and because of wet fuel conditions was effectively managed to achieve the same objectives as a prescribed fire

### 8.2.3 Effect Coefficients

This analysis quantifies an array of adverse health effects attributable to $PM_{2.5}$ and ozone exposures, including premature death and morbidity outcomes. For the main analysis, the chosen studies examine the health effects associated with ambient exposures to $PM_{2.5}$ and ozone and have been used in recent U.S. EPA benefits analyses. U.S. EPA recently published a Technical Support Document that provides a detailed description of the Agency's systematic evaluation of the epidemiologic literature and the concentration-response (C-R) relationships used to develop health impact functions (U.S. EPA, 2021). In summary for $PM_{2.5}$, analyses focus on the following outcomes: short-term $PM_{2.5}$ exposure and mortality, all ages (Zanobetti and Schwartz, 2009); long-term $PM_{2.5}$ exposure and mortality, ages 30−99 (Turner et al., 2016); respiratory-related emergency department (ED) visits, all ages (Krall et al., 2016); cardiovascular-related ED visits, all ages (Ostro et al., 2016); respiratory-related hospital admissions, ages 0−18 years (Ostro et al., 2009); and cardiovascular-related hospital admissions, ages 65 and over (Bell et al., 2015). For ozone, analyses focus on short-term ozone exposure and respiratory mortality, all ages (Katsouyanni et al., 2009); long-term ozone exposure and respiratory mortality, ages 30−99 (Turner et al., 2016); respiratory-related ED visits, all ages (Barry et al., 2019); and respiratory-related hospital admissions, ages 65 and over (Katsouyanni et al., 2009).

The analysis quantifies the same morbidity impacts for each case study scenario. However, because the length of the actual TC6 and Rough fires varied, the analysis quantifies mortality impacts differently for each case study. Because the TC6 Fire only lasted a few days, mortality impacts are quantified using a short-term $PM_{2.5}$ exposure function. However, because the Rough Fire lasted multiple months, mortality impacts are quantified using a long-term $PM_{2.5}$ exposure function. Mortality impacts due to short-term $PM_{2.5}$ exposure are not quantified in the Rough Fire case study analyses to prevent the double counting of mortality impacts.

Whereas the main analyses rely on health impact functions derived from epidemiologic studies of ambient $PM_{2.5}$ exposures, the sensitivity analysis examined whether estimated health impacts differed when using health impact functions derived from epidemiologic studies that specifically examined wildfire smoke exposure (i.e., wildfire-specific $PM_{2.5}$). In the sensitivity analysis, only respiratory and cardiovascular outcomes are quantified because among the epidemiologic studies evaluated in CHAPTER 6 (see Section 6.2), only these studies used an exposure indicator of wildfire $PM_{2.5}$ and were suitable for use within BenMAP–CE (i.e., were conducted in locations similar to the case studies and represented health outcomes with available incidence data). Of the available respiratory-related ED visits studies that used wildfire $PM_{2.5}$ as the exposure indicator, none examined all respiratory-related ED visits; as a result, the sensitivity analysis quantified asthma ED visits using a risk coefficient from a study conducted by Reid et al. (2019) in northern California. With respect to hospital admissions, respiratory-related hospital admissions were quantified using a risk coefficient from a study conducted by Gan et al. (2017) in Washington state, and cardiovascular-related hospital admissions were quantified using a risk coefficient from a study focusing on a wildfire event in southern California conducted by Delfino et al. (2009).

### 8.2.4 Baseline Incidence and Prevalence Data

The epidemiologic studies noted above report estimates of risk (i.e., effect coefficients or β coefficients) that are expressed as being relative to a baseline rate. In this analysis, these effect coefficients were used to quantify cases of ED visits, hospital admissions and premature deaths, and thus baseline rates of all-cause mortality, ED visits, and hospital admissions were used in the estimation of these health impacts. County-level age-stratified all-cause death rates were obtained from the Centers for Disease Control Wide-ranging ONline Data for Epidemiologic Research (WONDER) database (CDC, 2016) for the Year 2010, while ED visit and hospital visit rates were obtained from the Healthcare Cost and Utilization Program (HCUP), which consists of a mixture of county, state and regional rates.

### 8.2.5 Assigning $PM_{2.5}$ Concentrations to the Population

Changes in population-level exposure are quantified by assigning the predicted $PM_{2.5}$ concentrations to the U.S. census-reported population in each 4-km by 4-km model grid cell for the TC6 Fire case study and 12 km by 12 km in the Rough Fire case study (see CHAPTER 5 for a detailed description of the air quality modeling simulations). As a first step, the PopGrid population preprocessing tool was used to assign U.S. census-reported population counts at the census block level to each air quality model grid cell. These population counts were stratified by age, sex, race, and ethnicity. The census-reported population counts for the Year 2010 were used and then counts were projected to the Year 2020 using forecast population from Woods & Poole (2016).

To calculate wildland fire $PM_{2.5}$ concentrations, concentrations were weighted to the size of the population exposed to wildland fire $PM_{2.5}$ concentrations for all counties combined ($C_i$) in Year $i$ as

$$C_i = \frac{\sum_j^i C_{ij} \times P_{ij}}{P_i}$$

**Equation 8-2**

where $C_{ij}$ is the wildfire-attributable annual mean $PM_{2.5}$ concentration in county $j$ in Year $i$, $P_{ij}$ is the population in county $j$ in Year $i$, and $P_i$ is the total population over all counties combined in Year $i$.

### 8.2.6 Economic Analysis

The value of avoided premature deaths was estimated using a Value of Statistical Life (VSL) recommended by the U.S. EPA's Guidelines for Preparing Economic Analyses (U.S. EPA, 2014). Following U.S. EPA guidelines, this value was indexed to the inflation and income year of the analysis. Using a 2015 inflation year and assuming 2020 income levels, a VSL of $9.5 millions (M) was used. To value changes in respiratory hospital admissions, a cost of illness estimate was used, which is consistent with the approached used by the U.S. EPA in its Regulatory Impact Analysis for the $PM_{2.5}$ National Ambient Air Quality Standards (U.S. EPA, 2013). This value of $36,000 reflects the direct medical costs associated with the hospital visit as well as lost earnings. Following this same approach, we estimate the value of cardiovascular hospital admissions to fall between $41,000 and $42,000 depending on the age of onset. Finally, we quantify the value of emergency department visits using a simple average of two Cost of Illness values reported by Smith et al. (1997) and Stanford et al. (1999), which produces a value of $430.

## 8.3 Results from Case Study Fire Analyses

The sections present the estimated health impacts and corresponding economic values from the BenMAP–CE analyses for each of the actual fires, hypothetical scenarios, prescribed fires, and wildfire that yielded positive resource benefits for each case study. The main results presented in Section 8.3.1 are based on risk coefficients from epidemiologic studies used by U.S. EPA in previous benefits analyses as noted above; while Section 8.3.2 presents results from the sensitivity analyses using risk coefficients from studies examining wildfire-specific $PM_{2.5}$ and alternative epidemiologic studies examining ambient ozone exposure. Lastly, building off the discussion presented in CHAPTER 6 (see Section 6.3), Section 8.3.3 estimates the potential reduction in health impacts presented that could be achieved through the implementation of various actions or interventions to reduce or mitigate wildland fire smoke exposure.

### 8.3.1 Main Results

The estimated number and value of wildfire-related health impacts varies across the scenarios and the pollutant assessed. $PM_{2.5}$-attributable effects are consistently larger than those quantified for ozone. The estimated number of premature deaths, ED visits, and hospital admissions are larger for the Rough Fire scenarios than they are for the TC6 Fire scenarios; this can be attributed to differences in the magnitude of the fires, the duration of each fire, and the population density around each fire. For the TC6 Fire scenarios, fractional counts of air pollution-attributable effects are presented to illustrate the small, but meaningful, differences in impacts among the scenarios.

The dollar value of fires for the TC6 Fire case study is as large as $100 M while the value of the Rough Fire case study is as large as $3 billions (B). These values represent the sum of the medical costs and productivity losses associated with the ED visits and hospital admissions and the of value air pollution-attributable deaths. This latter value is quantified using a Value of Statistical Life, which is a measure of an individual’s willingness to pay to reduce the risk of dying prematurely by a small amount; it is not the value of any individual life.

## Table 8-2 Estimated counts of $PM_{2.5}$ premature deaths and illnesses (95% confidence interval).

| Case Study | Scenario | ED Visits: Respiratory | ED Visits: Cardiovascular | Hospital Admissions: Respiratory | Hospital Admissions: Cardiovascular | Mortality: Short Term | Mortality: Long Term |
|---|---|---|---|---|---|---|---|
| Timber Crater 6 (TC6) | **Actual fire** | 0.2 (0.0 to 0.4) | 0.1 (−0.0 to 0.2) | 0.0 (0.0 to 0.0) | 0.0 (0.0 to 0.1) | 0.04 (0.01 to 0.08) | --- |
| | Scenario 1 (small) | 0.1 (0.0 to 0.2) | 0.1 (−0.0 to 0.1) | 0.0 (0.0 to 0.0) | 0.0 (0.0 to 0.0) | 0.03 (0.01 to 0.5) | --- |
| | Scenario 2a (large) | 0.8 (0.2 to 1.6) | 0.4 (−0.1 to 0.9) | 0.1 (0.0 to 0.1) | 0.2 (0.1 to 0.2) | 0.16 (0.01 to 0.32) | --- |
| | Scenario 2b (largest) | 1.2 (0.2 to 2.5) | 0.6 (−0.2 to 1.3) | 0.1 (0.1 to 0.2) | 0.3 (0.2 to 0.3) | 0.25 (0.01 to 0.49) | --- |
| | Prescribed fires | 0.04 (0.01 to 0.08) | 0.02 (−0.01 to 0.05) | 0.00 (0.00 to 0.01) | 0.01 (0.01 to 0.01) | 0.01 (0.001 to 0.02) | --- |
| Rough Fire | Actual fire | 47.3 (9.3 to 98.5) | 19.7 (−7.6 to 46.0) | 6.9 (3.0 to 10.7) | 8.6 (6.2 to 10.9) | --- | 80.0 (53.6 to 105.4) |
| | Scenario 1 (small) | 28.2 (5.5 to 58.7) | 11.8 (−4.6 to 27.6) | 4.2 (1.8 to 6.5) | 5.0 (3.6 to 6.3) | --- | 48.1 (32.2 to 63.4) |
| | Scenario 2 (large) | 49.8 (9.8 to 103.7) | 20.7 (−8.0 to 48.4) | 7.3 (3.2 to 11.2) | 9.1 (6.6 to 11.5) | --- | 84.3 (56.5 to 111.1) |
| | Sheep Complex Fire | 6.6 (1.3 to 13.7) | 2.7 (−1.0 to 6.2) | 0.9 (0.4 to 1.4) | 0.9 (0.7 to 1.2) | --- | 10.1 (6.7 to 13.3) |
| | Boulder Creek Prescribed Fire | 1.1 (0.2 to 2.4) | 0.5 (−0.2 to 1.1) | 0.2 (0.1 to 0.3) | 0.2 (0.2 to 0.3) | --- | 1.9 (1.3 to 2.5) |

ED = emergency department; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; TC6 = Timber Crater 6.

**Table 8-3 Estimated counts of ozone ($O_3$) premature deaths and illnesses (95% confidence interval).**

| Case Study | Scenario | Respiratory ED Visits | Respiratory Hospital Admissions | Mortality | |
|---|---|---|---|---|---|
| | | | | Short Term | Long Term |
| Timber Crater 6 (TC6) | Actual fire | 0.06 (0.02 to 0.1) | 0.0 (−0.0 to 0.0) | 0.0 (−0.0 to 0.0) | -- |
| | Scenario 1 (small) | 0.03 (0.01 to 0.06) | 0.0 (0.0 to 0.0) | 0.0 (0.0 to 0.0) | -- |
| | Scenario 2a (large) | 0.10 (0.03 to 0.2) | 0.0 (−0.0 to 0.0) | 0.0 (−0.0 to 0.0) | -- |
| | Scenario 2b (largest) | 0.15 (0.04 to 0.3) | 0.0 (−0.0 to 0.0) | 0.0 (−0.0 to 0.0) | -- |
| | Prescribed fires | 0.01 (0.0 to 0.02) | 0.0 (0.0 to 0.0) | 0.0 (0.0 to 0.0) | -- |
| Rough Fire | Actual fire | 4.6 (1.3 to 9.6) | 0.2 (−0.05 to 0.4) | --- | 2.0 (1.4 to 2.6) |
| | Scenario 1 (small) | 1.7 (0.5 to 3.6) | 0.07 (−0.02 to 0.2) | --- | 0.9 (0.6 to 1.2) |
| | Scenario 2 (large) | 2.0 (0.05 to 4) | 0.06 (−0.02 to 0.1) | --- | 0.6 (0.4 to 0.8) |
| | Sheep Complex Fire | 0.8 (0.2 to 1.6) | 0.03 (−0.01 to −0.6) | ---- | 0.3 (0.2 to 0.4) |
| | Boulder Creek Prescribed Fire | 0.0 (0.0 to 0.0) | 0.0 (0.0 to 0.0) | --- | 0.0 (0.0 to 0.0) |

ED = emergency department; $O_3$ = ozone; TC6 = Timber Crater 6.

**Table 8-4 Estimated value of $PM_{2.5}$ and ozone-related premature deaths and illnesses (95% confidence interval; millions of 2015 dollars).**

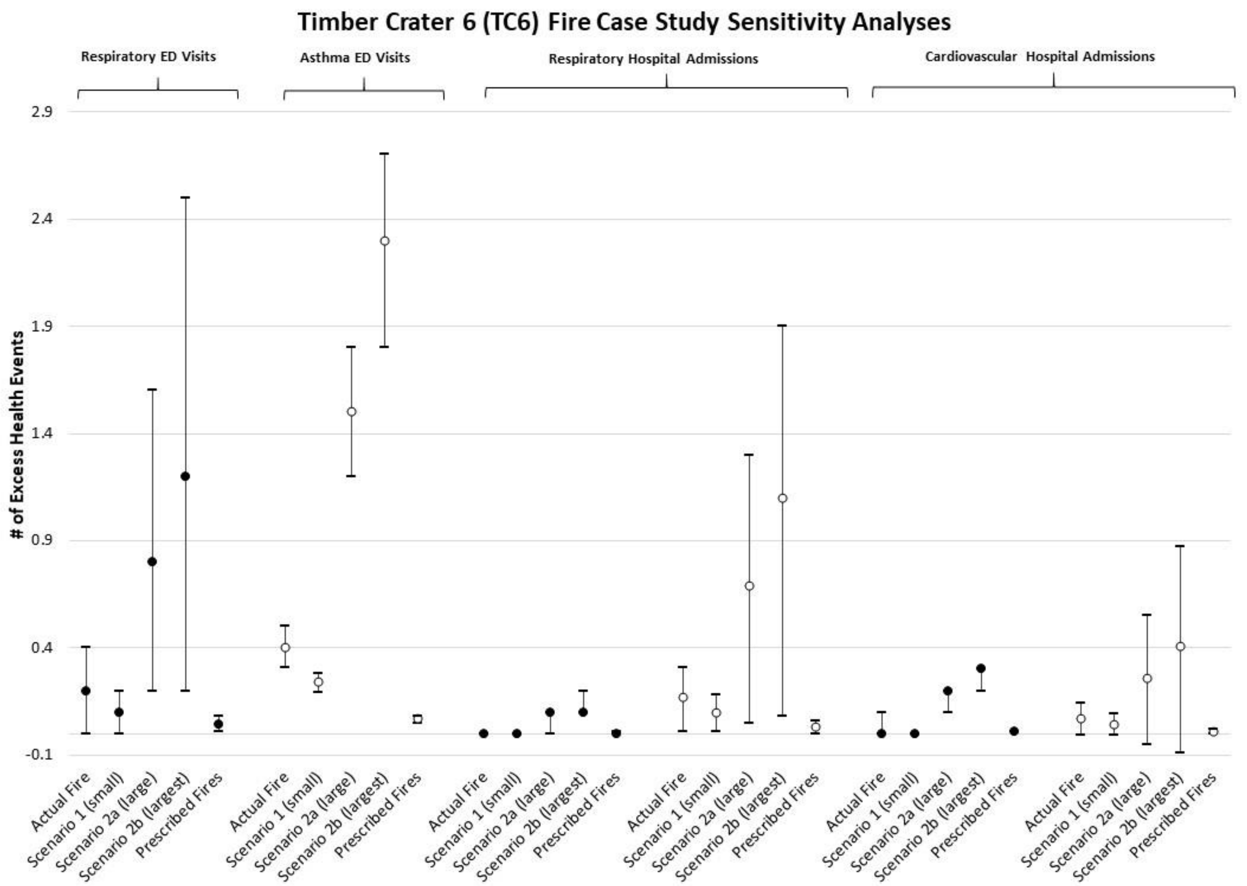
| Case Study | Scenario | Sum of Value of Morbidity Impacts and Value of: Short-Term Exposure Mortality ($) | Sum of Value of Morbidity Impacts and Value of: Long-Term Exposure Mortality ($) |
|---|---|---|---|
| Timber Crater 6 (TC6) | Actual Fire | 18 (2 to 47) | -- |
| | Scenario 1 (small) | 10 (1 to 26) | -- |
| | Scenario 2a (large) | 66 (6 to 170) | -- |
| | Scenario 2b (largest) | 100 (9 to 270) | -- |
| | Prescribed Fires | 4 (0 to 9) | -- |
| Rough Fire | Actual Fire | --- | 3,000 (260 to 7,900) |
| | Scenario 1 (small) | --- | 1,800 (160 to 4,700) |
| | Scenario 2 (large) | --- | 3,100 (270 to 8,300) |
| | Sheep Complex Fire | --- | 350 (20 to 960) |
| | Boulder Creek Prescribed Fire | --- | 60 (5 to 160) |

$PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

### 8.3.2 Sensitivity Analyses

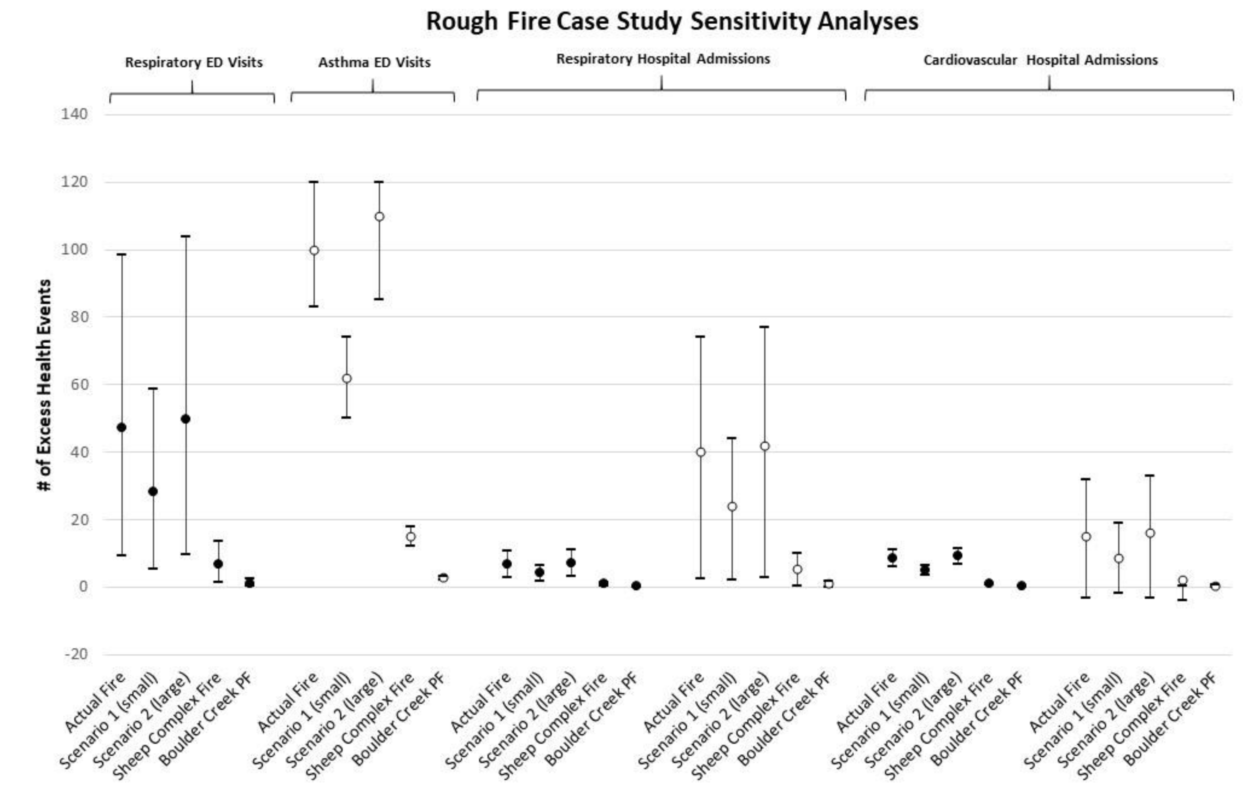
As noted above, the results presented within this section include estimates derived from health impact functions based on risk coefficients from epidemiologic studies that examined exposures to wildfire-specific $PM_{2.5}$ as a comparison to results from health impact functions based on ambient $PM_{2.5}$ exposures. Compared to the main analysis results, using the wildfire-specific $PM_{2.5}$ functions resulted in an increase in the estimated impacts for each case study (TC6: Figure 8-1; Rough Fire: Figure 8-2). This difference in estimated health impacts between studies examining ambient and wildfire-specific $PM_{2.5}$

exposures could be attributed to a steeper C-R relationship at the higher short-term $PM_{2.5}$ concentrations experienced during wildfire events or the behavior of individuals exposed to $PM_{2.5}$ during a wildfire event. However, additional research focused on examining the C-R relationship for wildfire smoke exposure is required to fully grasp the differences between the main analysis and sensitivity analysis results. The corresponding economic values from the sensitivity analyses are presented in Table 8-5, but these values are not directly comparable to the main analysis because the sensitivity analyses did not estimate premature deaths as noted in Section 8.2.3.




ED = emergency department; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

**Figure 8-1 Estimated health impacts from sensitivity analyses using health impact functions based on ambient $PM_{2.5}$ exposures versus wildfire-specific $PM_{2.5}$ exposures for the Timber Crater 6 (TC6) Fire case study.**




ED = emergency department; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

**Figure 8-2 Estimated health impacts from sensitivity analyses using health impact functions based on ambient $PM_{2.5}$ exposures versus wildfire-specific $PM_{2.5}$ exposures for the Rough Fire case study.**

**Table 8-5 Estimated value of wildfire-specific $PM_{2.5}$ illnesses (95% Confidence interval; 2015 dollars) from sensitivity analyses.**

| Case Study | Scenario | Sum of Value of Morbidity Impacts ($) |
|---|---|---|
| Timber Crater 6 (TC6) | Actual fire | 8,600<br>(−76 to 17,000) |
| | Scenario 1 (small) | 5,100<br>(−59 to 10,000) |
| | Scenario 2a (large) | 35,000<br>(−220 to 69,000) |
| | Scenario 2b (largest) | 54,000<br>(−500 to 110,000) |
| | Prescribed fires | 2,000<br>(−14 to 3,900) |
| Rough Fire | Rough Fire (actual) | 2,100,000<br>(−6,600 to 4,000,000) |
| | Rough Fire (Scenario 1) | 1,200,000<br>(−1,400 to 2,400,000) |
| | Rough Fire (Scenario 2) | 2,200,000<br>(−7,800 to 4,200,000) |
| | Sheep Complex Fire | 280,000<br>(−37,000 to 550,000) |
| | Boulder Creek Prescribed Fire | 58,000<br>(−1,300 to 130,000) |

$PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

### 8.3.3 $PM_{2.5}$ Exposure Reduction Sensitivity Analysis

In assessing the health impacts and associated economic values attributed to smoke exposure from the actual fires in each of the case study areas as well as the hypothetical scenarios, the underlying assumption is that the population is exposed to the ambient $PM_{2.5}$ and ozone concentrations estimated through the air quality modeling process for each case study (see CHAPTER 5). However, as detailed in CHAPTER 6, through communication efforts it is possible to provide information to the public regarding actions that can be taken to reduce or mitigate smoke exposure from wildfires or prescribed fires, which could ultimately reduce the overall public health impact of smoke.

Using the average overall exposure reduction that could be achieved due to various exposure reduction actions, presented in Table 6-1, the potential reduction in public health impacts that could be achieved are estimated for both case study fires, the corresponding hypothetical scenarios, and the prescribed fires (either actual or hypothetical) conducted in each location. The estimated overall reduction in total health impacts in Table 8-6 and Table 8-7 assume a linear relationship between population exposure concentrations and estimated health impacts such that the percent reduction in $PM_{2.5}$ exposure corresponds to an equivalent percent reduction in health impacts. Also as noted in Section 6.3.3, the reduction in health impacts presented in Table 8-6 and Table 8-7 correspond to an average overall exposure reduction based on data from available studies and accounts for both the magnitude of the intervention and the likelihood that this intervention is employed. The exposure reductions presented do not account for differences in communication efforts between wildfires and prescribed fires or that different concentrations may impact the likelihood of taking action as well as factors specific to the case study areas (e.g., population demographics and housing stock) that can influence the corresponding exposure reduction for these actions. Additionally, the estimation of the reduction in potential public health impacts attributed to smoke exposure for each actual fire is not meant to reflect a formal analysis of post-fire effectiveness of public health messaging by Air Resource Advisors (ARAs) deployed by the U.S. Forest Service, in combination with respective state and local air quality agencies, for either the TC6 or Rough fires, but instead an estimation of the potential implications of exposure reduction actions on reducing the overall public health impact of smoke.

**Table 8-6 Overall reduction in total health impacts attributed to $PM_{2.5}$ from wildfire smoke for the Timber Crater 6 (TC6) Fire case study.**

| Exposure Reduction Action (Overall Exposure Reduction; %) | Actual Fire | Hypothetical Scenarios 1 (small) | 2a (large) | 2b (largest) | Prescribed Fires |
|---|---|---|---|---|---|
| Total health impacts[a] | 0.34 | 0.23 | 1.66 | 2.45 | 0.08 |
| Stayed inside (31.8%) | −0.11 | −0.07 | −0.53 | −0.78 | −0.03 |
| Ran home HVAC system (24%) | −0.08 | −0.06 | −0.40 | −0.59 | −0.02 |
| Evacuated (24%) | −0.08 | −0.06 | −0.40 | −0.59 | −0.02 |
| Used air cleaner (15%) | −0.05 | −0.03 | −0.25 | −0.37 | −0.01 |

ED = emergency department; HVAC = heating, ventilation, and air conditioning; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

[a]Total number of health impacts represents the sum of ED visits, hospital admissions, and mortality detailed in Table 8-2; negative values in the table represent the estimated overall reduction in total impacts.

Corresponding 95% confidence intervals are not presented because these results represent and illustrative example.

**Table 8-7 Overall reduction in total health impacts attributed to $PM_{2.5}$ from wildfire smoke for the Rough Fire case study.**

| Exposure Reduction Action (Overall Exposure Reduction; %) | Rough Fire | Hypothetical Scenarios 1 (small) | Hypothetical Scenarios 2 (large) | Sheep Complex Fire | Boulder Creek Fire—Prescribed Fire[a] |
|---|---|---|---|---|---|
| Total health impacts[b] | 162.5 | 97.3 | 171.5 | 21.2 | --- |
| Stayed inside (31.8%) | −51.7 | −30.9 | −54.5 | −6.7 | --- |
| Ran home HVAC system (24%) | −39.0 | −23.4 | −41.2 | −5.1 | --- |
| Evacuated (24%) | −39.0 | −23.4 | −41.2 | −5.1 | --- |
| Used air cleaner (15%) | −24.4 | −14.6 | −25.7 | −3.2 | --- |

ED = emergency department; HVAC = heating, ventilation, and air conditioning; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

[a]The health impacts for the Boulder Creek analysis were negative, hence they are not reported in this table.

Corresponding 95% confidence intervals are not presented because these results represent and illustrative example.

[b]Total number of health impacts represents the sum of ED visits, hospital admissions, and mortality detailed in Table 8-2; negative values in the table represent the estimated overall reduction in total impacts.

## 8.4 Summary

The analyses presented within this chapter estimate the potential public health impacts and associated economic values attributed to smoke exposure, focusing specifically on $PM_{2.5}$ and ozone, from wildland fire within the case study areas of the TC6 and Rough fires. Analyses for both case studies, which build off the assessment of the air quality impacts of each actual fire, hypothetical scenarios, and prescribed fires presented in CHAPTER 5, demonstrate that health impacts are dominated by exposure to $PM_{2.5}$ from wildland fire smoke.

The results of the case study analyses indicate that proximity to population centers and atmospheric conditions (e.g., wind patterns) influence the magnitude of health impacts attributed to smoke. Building off the air quality modeling analyses presented in CHAPTER 5 that depict differences in both $PM_{2.5}$ concentrations and population exposures, the corresponding BenMAP–CE analyses indicate that fire management strategies targeted to reduce the spread and overall size of wildfires, as depicted in the smaller hypothetical fires, can result in substantial differences in the health impacts and corresponding economic values when compared to the actual fires. Even though prescribed fires in both case study areas, and wildfires managed for resource benefits (i.e., Sheep Complex Fire), are shown to contribute to an estimated reduction in health impacts from wildfires, it is important to recognize that these fires are not without risk and do also contribute to health impacts, albeit smaller in number.

Sensitivity analyses that explore potential differences in estimated health impacts between health impact functions derived from epidemiologic studies of ambient $PM_{2.5}$ and wildfire-specific $PM_{2.5}$, provide evidence of potentially larger estimated impacts when using wildfire-specific $PM_{2.5}$ health impact functions. Additional analyses that provide a crude estimation of the potential implications of actions or interventions to reduce and mitigate wildland fire smoke exposure demonstrate the potential public health benefits of messaging campaigns to the public. However, for both sensitivity analyses, additional research is warranted to more fully assess the implications of using ambient and wildfire-specific $PM_{2.5}$ health impact functions, and to provide a more representative estimation of the potential public health benefits of actions or interventions to reduce wildfire smoke exposure.

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# CHAPTER 9 INTEGRATED SYNTHESIS

## 9.1 Introduction

The focus of this chapter is to summarize and synthesize the information presented in the previous chapters that either directly informed the quantitative analyses examining the air quality impacts and corresponding health impacts of smoke from wildland fire (i.e., wildfire and prescribed fire) under different fire management strategies, or provided ancillary information that allowed for the overall results of the analyses to be put into the proper context.[5] Overall, this assessment demonstrates the successful application of a novel modeling approach in the examination of two case study fires to provide a quantitatively estimate the differences in air quality and health impacts based on different fire management strategies.

In theory, an assessment of the air quality impacts and the corresponding human health impacts of prescribed fire compared to wildfire may seem relatively straightforward. However, the question is layered with complexities in both the development of analyses and the interpretation of results due to numerous factors including spatial and temporal differences between prescribed fire and wildfire along with the overall management objectives of each (i.e., either suppression objectives or resource objectives), which is dynamic and can change daily depending on various factors (e.g., fire behavior, as detailed in CHAPTER 2 and CHAPTER 3). As a result, it is important to recognize that while the analyses conducted within this report represent an incremental advancement in the overall understanding of the health implications of smoke from wildland fire on surrounding populations, the results are based on a novel modeling approach that required assumptions and decisions based on expert judgment, particularly with respect to fire spread in the design of hypothetical scenarios for each case study.

The preceding chapters of this report were organized around characterizing the components that are important to consider in the process of examining the air quality impacts and corresponding health impacts of smoke from wildland fire under different fire management strategies. In estimating differences between the air quality impacts of prescribed fire and wildfire, this assessment took a holistic approach of identifying all of the factors and impacts (both positive and negative) that should be accounted for in the process of examining different fire management strategies through the development of a conceptual framework (CHAPTER 2; Figure 2-1, Figure 9-4 in this chapter). CHAPTER 3 through CHAPTER 8 then described the current state of the science with respect to implementing this framework with the goal of employing the best available science and data to estimate as many of those impacts as feasible. A fuller

[5] Within this assessment, the term "impacts" refers to the main quantitative results, which includes the estimated air pollutant concentrations from the air quality modeling and the number of health events and associated economic values calculated using U.S. Environmental Protection Agency's (U.S. EPA's) Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP–CE). The term "effects" is used to denote the other positive and negative consequences of wildland fire.

accounting of benefits and costs of fire management strategies, which is not the focus of this assessment, would quantitatively address the remaining components of the conceptual framework, including management costs, direct fire effects, and ecological effects.

While the results of this assessment are extremely informative in addressing the larger question of whether there are differences in the public health impacts of wildland fire smoke for different fire management strategies, it is also important to ensure the results are interpreted appropriately and to recognize that the effects characterized represent only a portion of the broader societal, human health, and ecological effects of wildland fire events. Therefore, subsequent sections of this chapter provide an overview of the results of the analyses; broadly assesses the limitations and uncertainties surrounding the examination of the air quality and corresponding public health impacts of prescribed fire and wildfire; identifies the limitations and gaps in knowledge and data that shaped the implementation of the conceptual framework (Figure 9-4); highlights key insights from the case study analyses; and outlines additional areas of research that could further enhance the characterization of the impacts of smoke from wildland fire.

## 9.2 Overview of Results

The overall goal of the case study analyses conducted within this assessment is twofold: (1) develop a modeling framework to examine the air quality and health impacts of smoke from wildland fire under different fire management strategies and (2) demonstrate the application of the modeling framework for wildfires that encompass different spatial and temporal scales. Because the analyses conducted within this assessment focus on wildfires of different spatial extent that occurred in two different geographic locations (i.e., Oregon and California), it is important to clearly note that the results are specific to the locations of the two case study fires and the land management practices that were used prior to both fires occurring. Therefore, the results of these analyses cannot be extrapolated to other geographic locations without consideration of differences in land management practices (including history) and environmental variables (e.g., geography, vegetation, fire regime, climate, and weather).

Across each of the case studies, the air quality modeling, and subsequently health impact analyses using U.S. Environmental Protection Agency’s (U.S. EPA’s) Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP–CE), clearly depicts that air quality impacts attributed to wildland fire smoke are dominated by changes in fine particulate matter ($PM_{2.5}$; particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm) concentrations (see Section 5.3). Although ozone is formed downwind of a smoke plume as a result of many of its precursors being emitted in wildland fire smoke (see CHAPTER 4 and CHAPTER 5), the incremental contributions to concentrations often do not result in substantial public health impacts. This is because the magnitude of population-level health impacts depends on the intersection of smoke plumes that have elevated $PM_{2.5}$ and ozone concentrations over time with population density. Fires that result in smoke plumes, or elevated ozone concentrations downwind of a smoke plume, that do not intersect with high population areas or last only a few days are less likely to have as substantial health impacts as fires affecting larger populations for longer periods. This concept of duration of fire multiplied by population density represents the main driver behind the difference in results between the Timber Crater 6 (TC6) and Rough fire case studies discussed in more detail below.

As a reminder, both case study fires were selected because they occurred on federal land and were managed by multiple federal agencies. Additionally, the TC6 Fire was selected because there is extensive data that had been collected on the land management practices employed, including prescribed fire activity, within the area, and in combination with the small size of the fire, allowed for a finer resolution analysis (i.e., at the 4-km scale). In comparison, the Rough Fire was selected to provide an examination of a larger fire, in terms of duration and size, but there was no actual prescribed fire activity in the area. However, with the Sheep Complex Fire yielding positive resource benefits and detailed information available on the proposed Boulder Creek Prescribed Fire it was possible to develop hypothetical scenarios for the Rough Fire case study that were consistent with the hypothetical scenarios developed for the TC6 Fire case study (i.e., a smaller and larger fire based on different land management strategies).

### 9.2.1 Timber Crater 6 (TC6) Case Study

The analysis of the TC6 Fire case study focused on estimating the air quality and health impacts attributed to the actual TC6 Fire, as well as hypothetical TC6 Fire scenarios based on assumptions surrounding fire spread and fuel availability that was rooted in the detailed land management data for the area (see Section 5.1.3), resulting in the following hypothetical scenarios:

- Hypothetical Scenario 1 (small): a smaller hypothetical TC6 Fire in a heavily managed area (i.e., most prescribed fire), which would equate to a wildfire with less fuel, a smaller fire perimeter, and less daily emissions
- Hypothetical Scenario 2a (large): a larger hypothetical TC6 Fire, but not the "worst-case" scenario, due to no land management which would equate to a wildfire with more fuel, a larger fire perimeter, and more daily emissions
- Hypothetical Scenario 2b (largest): a much larger, hypothetical "worst-case" scenario TC6 Fire with no land management (i.e., no prescribed fire) which would equate to a wildfire with the most fuel, largest fire perimeter, and largest daily emissions

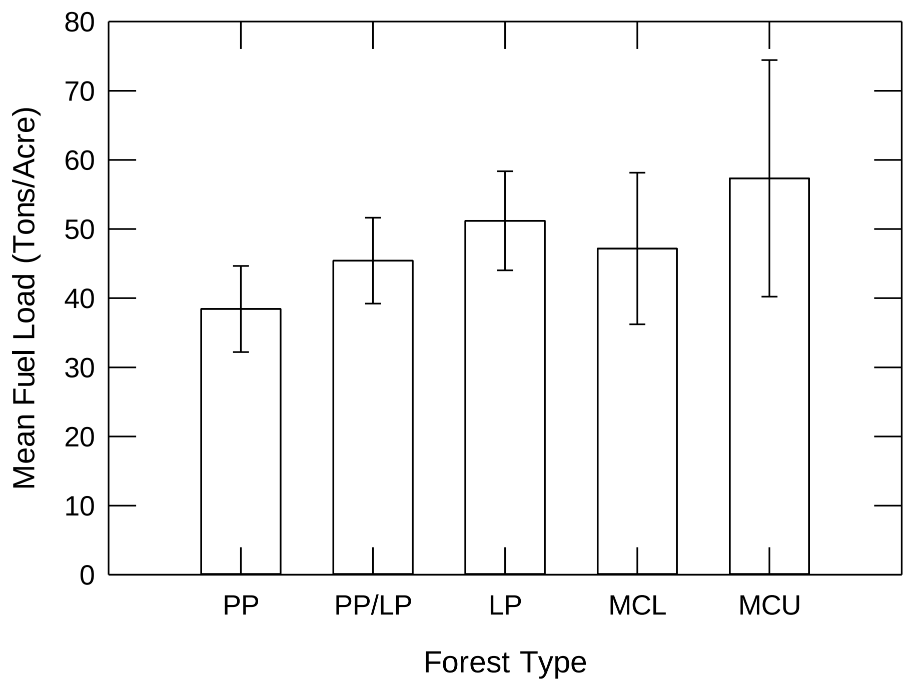
Even with the detailed land management data available, in devising the hypothetical scenarios for this case study, expert judgment was used to determine the daily fire perimeters and the overall burn perimeter for each scenario, which was influenced by the prescribed fire history within the area.

One of the main differences between the TC6 Fire and Rough Fire case studies was the availability of data on prescribed fire activity. Although there was information on the prescribed fire activity within the vicinity of the TC6 Fire that could have impacted the spread of the fire, these fires occurred over many years, with one dating back to 1978 (see Section 5.1.4). As a result, to compare the prescribed fire smoke impacts with the actual TC6 Fire and hypothetical scenarios, all prescribed fire activity was modeled for the same month and year (i.e., September 2019). This approach was used because there was detailed data both on the days in September 2019 that fit prescription requirements and for which a prescribed fire occurred. However, employing this strategy does not take into consideration the rate of prescribed fire activity and ignores the episodic nature of prescribed fires compared to wildfires, which is one of the overarching challenges of an analysis devised to compare the air quality and health impacts of prescribed fire to wildfire (see Section 9.3.1).

The air quality modeling demonstrates that there are clear differences in the air quality impacts between the actual TC6 Fire and each of the hypothetical scenarios, with the larger fire scenarios (Hypothetical Scenarios 2a and 2b) resulting in higher concentrations for a longer duration, specifically for $PM_{2.5}$. This observation is also consistent when comparing the actual TC6 Fire and hypothetical scenarios with the air quality impacts from the prescribed fires. The difference in the modeled air quality impacts between the prescribed fires and the actual TC6 Fire and hypothetical scenarios can be attributed to the short duration of each prescribed fire combined with the fact these fires were scheduled on days that met specific criteria aimed at minimizing population exposure (e.g., meteorology conducive for ventilation and dilution of pollutants).

While there are differences in air quality impacts across each of the scenarios examined, within the vicinity of the TC6 Fire, population density is relatively small, and the examination of aggregate population exposures which combines the influence of daily weather patterns, fire duration, and population proximity to fires, shows that the overall potential public health impacts attributed to smoke exposure would be small relative to larger fires (see Section 5.3.1; see Figure 5-10 and Figure 5-11). This observation from the air quality modeling is reflected in the BenMAP–CE analysis for the actual TC6 Fire and the hypothetical scenarios where the overall health impacts and corresponding economic values are small (see Table 8-2, Table 8-3, and Table 8-4). From a health impact perspective while the overall values are <1 for most health outcomes for $PM_{2.5}$, and for all health outcomes for ozone across each fire type, when examining the economic impact there is a more notable difference between the actual TC6 Fire, prescribed fires, and each hypothetical scenario. This difference reflects the high value placed on reductions in the risk of premature death. Even small changes in risk can have economic value because one statistical premature death is valued at $9.5 million.

Although the small smoke-related health impacts from the TC6 Fire can be attributed to the small population density within the case study area, the land management activities employed over time were instrumental in reducing the fuel available and the overall fire perimeter, which equated to smaller air quality impacts. Untreated forests within the TC6 Fire case study area are characterized by high fuel loads (live and dead) that pose significant challenge to fire managers. Combined with hot, dry summers and few natural barriers to fire spread, these spatially contiguous fuel loads create conditions ripe for large fire growth. Baseline surface fuel loads (dead and down biomass) in untreated stands vary along a productivity gradient, ranging from an average of 38 tons per acre in pure ponderosa pine to 46 tons per acre in mixed ponderosa pine/lodgepole pine forests (the most widespread type), and up to 56 tons per acre in the more productive upper elevation mixed conifer forest types (see Figure 9-1). Standing tree densities (live and snags) averaged 881 to 2,899 trees per hectare across the same gradient. These conditions were typical of what was encountered during the rapid initial growth of the TC6 Fire where no fuels treatments had occurred. The extensive fuel treatment network employed in other parts of the area prevented these conditions from occurring across the entire TC6 Fire footprint.




TC6 = Timber Crater 6.

Note: Forest types from left to right are: PP = ponderosa pine (n = 4 plots), PP/LP = mixed ponderosa/lodgepole (n = 5), LP = lodgepole pine (n = 9), MCL = lower mixed conifer (n = 13), MCU = upper mixed conifer (n = 8).

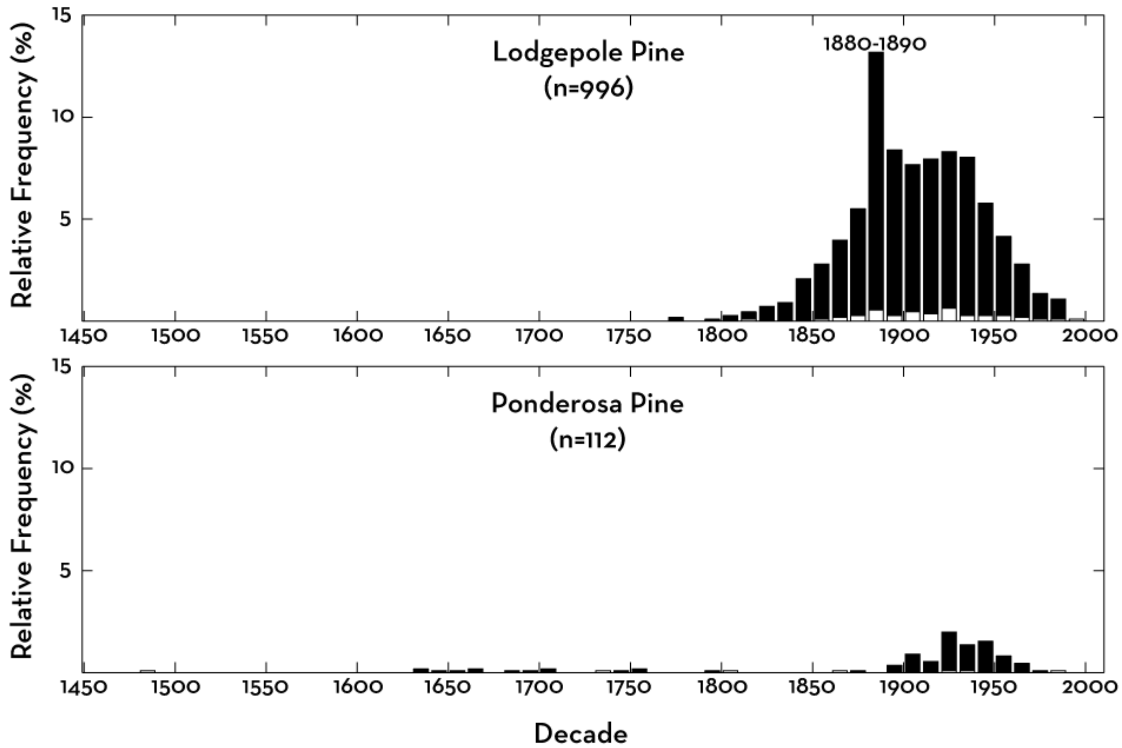
Source: National Park Service Long-Term Monitoring Plots (Farris, 2017).

**Figure 9-1 Surface fuel loading in untreated forests in the Timber Crater 6 (TC6) Fire study area in Crater Lake National Park.**

This high contemporary fuel loading within the TC6 Fire case study area is an artifact of more than a century of ubiquitous fire exclusion in the region beginning in the late 1800s. Prior to about 1890, fires were frequent across this landscape and resulted in limited broad-scale tree density and surface fuel accumulation. Hagmann et al. (2019) recently conducted a detailed fire history study just 30 km east of the TC6 Fire area consisting of nearly identical terrain and forest composition. They found that years in which fires burned >20,000 hectares occurred every 9.5 years on average for the period 1700 to 1918, and seven fire years burned >40,000 hectares. These large, predominantly low-intensity fires were associated with drought years; more frequent but smaller fires occurred in interim periods. At a finer scale, fire frequency and intensity varied along gradients of productivity and surface fuel continuity ranging from 7 to 25 years. Most high severity burning was restricted to pockets of dense lodgepole pine. This pattern resulted in relatively small patch mosaics of denser stands within a matrix of open, low density stands. This same gradient occurs in the TC6 Fire study area and is consistent with a description of fire occurrence and fire severity mosaics by Agee (1981).

The cessation of frequent low intensity fires across the greater Pumice Plateau Ecoregion in central Oregon began in the late 1800s but varied locally (Omernik and Griffith, 2014). Initially, extensive fire exclusion occurred indirectly as a result of changing land uses (such as heavy grazing and logging and development) and the displacement of Native American populations. Direct fire suppression activities continued with the onset of formal fire suppression activities in the early 1900s. Heyerdahl et al. (2014) and Merschel et al. (2018) documented sharp declines in fire occurrence in similar forests approximately 100 km north in the 1880s. Hagmann et al. (2019) also documented declines beginning in the late 1800s adjacent to the TC6 Fire area. There was a single large fire in 1918, but even this fire did not impact the TC6 Fire footprint.

The results of Heyerdahl et al. (2014), Merschel et al. (2018), and Hagmann et al. (2019) are consistent with local tree demography and recruitment data from Crater Lake National Park. In a 200-hectare study area burned by the TC6 Fire (along the U.S. Forest Service [USFS]/National Park Service [NPS] boundary) Kipfmueller (2014) documented a major pulse in tree recruitment in the 1880s, with high levels of recruitment continuing through the 1950s in the absence of fire (Figure 9-2). This recruitment pulse likely reflects a widespread fire exclusion signature and is consistent with the onset of major recruitment pulses elsewhere in Crater Lake National Park (Forrestel et al., 2017). High contemporary fuel loads in the study area are a direct legacy of this broad fire-exclusion recruitment cohort. In the absence of 20th century fires, this cohort created high tree densities across the formerly more heterogenous mosaic of productivity gradients. Many of these trees were converted to surface fuels following density-dependent thinning and periodic insect outbreaks in recent years. Moreover, continuous vertical fuel continuity from extensive ladder fuels create high crown fire initiation risk.




ha = hectare.
Source: Kipfmueller (2014).

**Figure 9-2 Decadal-scale representation of the age structure of lodegpole pine (LP) and ponderosa pine (PP) aggregated for a 200-ha study area within the Timber Crater 6 (TC6) Fire perimeter.**

Despite the high potential for major fires in the area, fire suppression was largely successful in the TC6 landscape as most ignitions were kept small (some of which were aided by the fire management strategies employed within the area). For example, in 2011 alone, there were seven lighting fires suppressed within 4 km of the TC6 Fire ignition. Thus, the only substantial burned acreage and reduction in fuel loads on the NPS side resulted from management-ignited prescribed burning and a lightning fire that yielded positive resource benefits (these efforts have been focused along the park boundary to facilitate future management of more lightning fires). On the USFS side, a combination of prescribed burns and mechanical fuels treatments have reduced fuel loads. Prescribed burning has reduced surface fuel loads by an average of 20% in low-productivity ponderosa pine to an average of 69% in lodgepole pine forests. Corresponding tree densities have been reduced by an average of 25% in ponderosa pine to 78% for lodgepole pine. The duration of treatments varies across a productivity gradient, but typically reach 75% of prefire levels within 15 years on productive sites. The fire management challenges and impacts of fire suppression fuel loading and potential fire behavior in the TC6 Fire area are similar to other coniferous forest types in the western U.S.

### 9.2.2 Rough Fire Case Study

The Rough Fire was selected because it represented a much larger fire than the TC6 Fire in terms of both area burned (i.e., ~150,000 acres) and duration (i.e., lasting ~2 months), which directly influenced the amount of smoke produced and the potential for a larger aggregate population exposure. However, compared to the TC6 Fire, there was more limited data available regarding previous land management practices within the vicinity of the Rough Fire to inform the development of hypothetical scenarios. As a result, the hypothetical scenarios devised for the Rough Fire are not based on the same type of land management strategies employed in the TC6 Fire case study. Specifically, the reliance on a wildfire that burned at lower intensity and yielded positive resource benefits (i.e., Sheep Complex Fire) and a proposed prescribed fire that did not occur as planned (i.e., Boulder Creek Prescribed Fire). However, the use of the proposed Boulder Creek Prescribed Fire and the Sheep Complex Fire achieved the same function of being able to devise Rough Fire hypothetical scenarios indicative of a smaller and larger Rough Fire, respectively, due to different land management strategies. The hypothetical scenarios for the Rough Fire consisted of the following:

- Hypothetical Scenario 1 (small): a small hypothetical Rough Fire that represents the combined impact of the proposed Boulder Creek Prescribed Fire and the Sheep Complex Fire, a wildfire that yielded positive resource benefits, on reducing the overall size of the Rough Fire
- Hypothetical Scenario 2 (large): a large hypothetical Rough Fire that allows for the fire perimeter of the Rough Fire to progress into the area of the Sheep Complex Fire as if both the Boulder Creek Prescribed Fire and Sheep Complex Fire did not occur

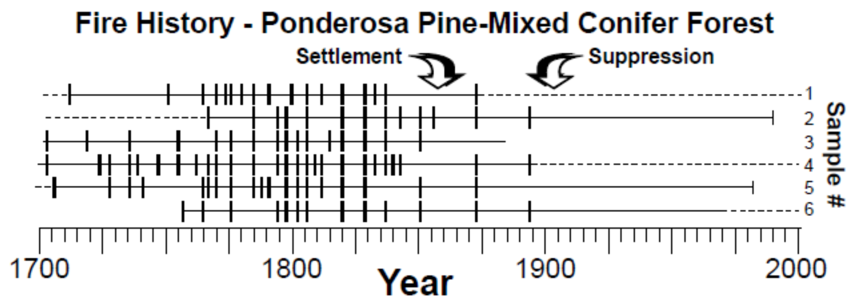
Similar to the TC6 case study, when examining air quality impacts for the actual Rough Fire and each hypothetical scenario, overall aggregate population exposures are greatest for $PM_{2.5}$ (Figure 5-15) even though ozone concentrations in this case study impact a larger geographic area. This difference can be attributed to ozone only being produced through secondary atmospheric reactions downwind from smoke events, whereas, $PM_{2.5}$ is not only directly emitted by fires, which represents the predominate downwind exposure, but it can also be produced through secondary atmospheric reactions. For both $PM_{2.5}$ and ozone a similar temporal pattern of concentrations is observed between the actual Rough Fire and hypothetical scenarios until later weeks in the duration of each fire, where there is a substantial reduction in concentrations for Hypothetical Scenario 1 (small fire, Figure 5-17). Although there was not an actual prescribed fire in the vicinity of the Rough Fire, air quality analyses of the proposed Boulder Creek Prescribed Fire (Figure 5-19) and the Sheep Complex Fire (Figure 5-20), exhibit a shorter duration and smaller exposure to $PM_{2.5}$, respectively, compared to the actual fire and hypothetical scenarios.

The differences in the public health impacts between the actual fire, hypothetical scenarios, a prescribed fire (i.e., Boulder Creek Prescribed Fire), and a wildfire that yielded positive resource benefits (i.e., Sheep Complex Fire) are depicted in Table 8-2. The health impacts of the actual Rough Fire, which reflects the occurrence of the Sheep Complex Fire, are relatively similar to hypothetical Scenario 2 (large fire), which assumes the Sheep Complex Fire did not occur. This similarity can be attributed to the Sheep Complex Fire not substantially affecting the overall spread and fire perimeter of the actual Rough Fire.

However, the results of Hypothetical Scenario 1 (smaller fire) demonstrates the potential benefit that could occur, specifically the reduction in fire spread and perimeter, by strategically planning the location of a prescribed fire. The modeling of the Boulder Creek Prescribed Fire shows that had that prescribed fire occurred on the outskirts of the Sheep Complex Fire perimeter, it could have prevented the spread of the Rough Fire, reducing air quality impacts and resulting in an approximate 40% reduction in health impacts. However, it is important to recognize that both the Sheep Complex Fire and the Boulder Creek Prescribed Fire scenarios did have detrimental effects on both air quality and health, although those effects were smaller than those estimated for the actual Rough Fire and each hypothetical scenario.

In addition to the air quality and health impacts observed between the different hypothetical scenarios of the Rough Fire case study, it is also important to take into consideration the impact of different land management strategies on the forest ecology around the case study area. Beyond the analogous examples in other parts of the U.S., the particular fire ecology and history of the dry forests of the Sierra Nevada Mountain offer more context for the analysis of the Rough Fire area, and illuminates how the results of the Rough Fire case study might be used to further understand how to minimize air quality impacts from wildfire smoke, both in this area and in other dry forest regions. There is substantial fuel available in these large, highly productive, west-facing Sierra Nevada drainages that can be released into the air all at once, as witnessed during the Rough, Rim, and any number of megafires (i.e., fires with >100,000 acres burned).

The spatial configuration, not just the amount of fuel is important as well. Fire adapted forest stands are characterized not only by lower fuel loads, but fuels that are "packaged" into fire adapted-clumps (also known as resilient forest structure) with gaps in between those clumps, resulting in fire that burns more slowly across the land, rather than all at once. At larger landscape scales, a mosaic of frequent, smaller, slower growing fires can contribute to reducing the number of megafires. Historically and prehistorically there is overwhelming evidence that the forests of the Sierra Nevada, including the area where the Rough Fire burned, experienced frequent burning. Local fire-scar chronologies indicate that most fire years prior to the 20th century were characterized by relatively small, spatially clustered fire events that were even smaller than the Sheep Complex Fire (Figure 9-3). Widespread fire events also occurred periodically during severe droughts, as indicated by synchronous scarring across multiple sample sites (Swetnam et al., 2009). While there is uncertainty about the size or extent of these large fire years, a major difference versus contemporary large fires is that they consisted predominantly of low-severity burning (Mallek et al., 2013).




Note: Reconstruction of past fire occurrence (tic marks) from fire scarred trees at six sites in the mixed conifer zone from 1700−2000.
Source: Sequoia & Kings Canyon National Parks (2005), copyright permission pending.

**Figure 9-3 Decline in fire frequency in mixed conifer forest (from nearby Sequoia and Kings Canyon National Parks) starting around 1860.**

Impacts to air quality from these fires would have likely been similar in intensity, duration, and spatial extent to impacts from the modeled Boulder Creek Prescribed and/or Sheep Complex fires, rather than the Rough Fire, both because such fires spread more slowly and because the fuels over the area in which they burned were substantially less than those currently observed in areas where fuels have accumulated after 100 years of fire suppression (Stephens et al., 2018). Additionally, these smaller, frequent fires created a landscape-scale mosaic of fire footprints, wherein fires were limited in their size by the footprints (and the removal of fuel within those footprints) of previous recent fires (Collins et al., 2009).

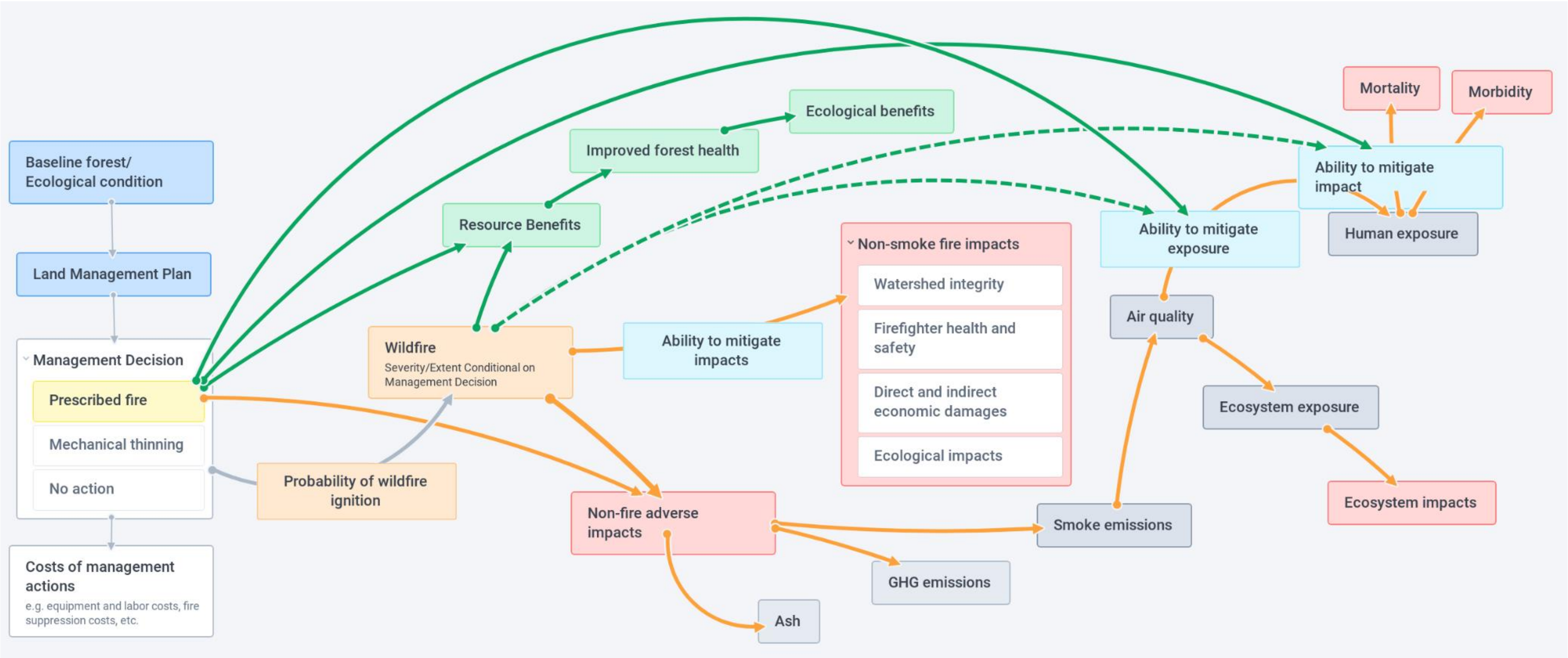
The hiatus from regular fire for the past 100 years has left substantial accumulated fuel on Sierra Nevada forested landscapes, and as a result, frequent, small, regular fires are not feasible, leading to a high potential for megafires (Stephens et al., 2018; Liu et al., 2016). The Sheep Complex Fire, compared to these megafires like the Rough Fire, was quite small, but the cool, wet conditions under which it was managed limited its ability to spread despite that fuel loading. Resulting air quality and public health impacts were limited directly during the burning of Sheep Complex in 2010, but also contributed to some reductions in impacts subsequently as the Rough Fire ran into its footprint in 2015. This illustrates the principle that even limited and opportunistic reintroduction of fire to a landscape can reduce the overall footprint of future fires, resulting in quantifiable air quality and public health benefits.

So far, at least in this case study, this work appears to qualitatively corroborate previous case study analyses [e.g., Long et al. (2018); Schweizer and Cisneros (2014); Cisneros et al. (2012)] showing that daily emissions were much lower compared to those during the Rim fire, which, like the Rough Fire, was ultimately contained by leveraging reduced fuels and fire behavior in previous fire footprints (Long et al., 2018). A limitation of the Rough Fire analyses is the regional-scale resolution (12-km-sized grid cells) of the air quality modeling. This spatial resolution may not fully capture pollutant dispersion in areas with complex terrain, such as the area of the Rough Fire, Sheep Complex Fire, and Boulder Creek Prescribed Fire. When the model does not capture complex meteorology it is possible emissions from a fire could be unrealistically dispersed over a larger area than would happen in reality and result in an overestimation of impacts downwind of the fire and underestimate impacts at the fire itself. Implications for this analysis would depend on the degree of over or underestimation of impacts in highly populated areas of the central valley of California. Future work using higher resolution modeling (e.g., 2-km resolution), and including a robust comparison of model predictions of $PM_{2.5}$ to observed could provide a more refined assessment of the magnitude of trade-offs between the Rough Fire scenarios presented within this assessment.

In summary, in dry forest ecosystems, such as in the area of the Rough Fire, these landscapes will experience some combination of prescribed fire and wildfire. The methodology for assessing public health trade-offs of different fire management strategies developed in this assessment, if deployed on a broader scale, landscape level analysis, could inform development of management strategies that incorporate protection of regional air quality and public health.

## 9.3 Limitations in Examining Differences between Prescribed Fire and Wildfire Impacts

Throughout this assessment, each chapter characterized the various components of the conceptual framework presented in CHAPTER 2 (Figure 2-1, and also presented below Figure 9-4) to varying degrees with some presenting a qualitative characterization of the state of the science, and others providing a quantitative analysis specific to the case study areas. In identifying limitations in the analyses, it is first necessary to review the information presented within each chapter and note which components of the conceptual framework could be addressed broadly and more specifically within each of the case study analyses (Section 9.3.1.). This approach then allows for a discussion of the overarching limitations of the analysis (Section 9.3.2.) followed by a discussion of current gaps in the scientific literature that were identified within this assessment (Section 9.3.3.). As the frequency of wildfires continues to grow, along with the frequency of prescribed fire as a land management strategy, it is important to consider these limitations and data gaps in the process of further refining the types of analyses conducted within this report and in advancing the overall understanding of the impacts of wildland fires.




Note: This is the same figure presented in CHAPTER 2, Figure 2-1. In the figure, forest management inputs are colored dark blue, management decisions and their nonsmoke related effects are colored white, resource benefits are colored green, mitigation actions are colored light blue, fires are colored yellow and orange, fire damages are colored red, and smoke exposure related elements are colored gray. The green arrows indicate positive effects, and the orange arrows indicate negative effects. Dotted lines represent linkages that may occur but are less certain that solid lines.

**Figure 9-4 Conceptual framework for evaluating and comparing fire management strategies.**

### 9.3.1 Implementing the Conceptual Framework

The ability to implement the conceptual framework, originally outlined in CHAPTER 2, and the degree to which quantitative information specific to the case study areas is available represents a key aspect of the quantitative estimation of air quality impacts associated with different fire management strategies. Each chapter presents information that is highly relevant to an assessment of the air quality impacts between different fire management strategies; however, in many instances this information is not specific to the case study areas and requires some degree of extrapolation.

Within this assessment, qualitative discussions are presented for multiple components of the conceptual framework due to a lack of quantitative information specific to the case study areas. Moving from left to right across the conceptual framework (Figure 2-1, and also Figure 9-4), CHAPTER 3 captures many of these initial components. This includes the baseline forest/ecological conditions of ecosystems similar to the case study areas, provides background information on different fire management decisions, and a history of fire activity, including the implementation of prescribed fire. In addition, the qualitative discussion in CHAPTER 3 highlights the instances where a wildfire can yield resource benefits, which are quantitatively evaluated in the Rough Fire case study through the modeling of the Sheep Complex Fire (CHAPTER 5 and CHAPTER 8), and discusses how fire on the landscape can contribute to improved forest health and result in ecological benefits.

The direct fire impacts of wildfire (CHAPTER 7), including firefighter health and safety, and societal impacts including economic and ecological and welfare effects, while important to consider broadly when making comparisons amongst different fire management strategies cannot be quantified at the case study level. Although there are opportunities to mitigate these direct fire effects, they are not accounted for within this assessment. The nonfire effects, which include greenhouse gas (GHG) emissions (CHAPTER 3) and ash deposition (CHAPTER 6), are characterized qualitatively to varying degrees, including the ecological effects of ash deposition.

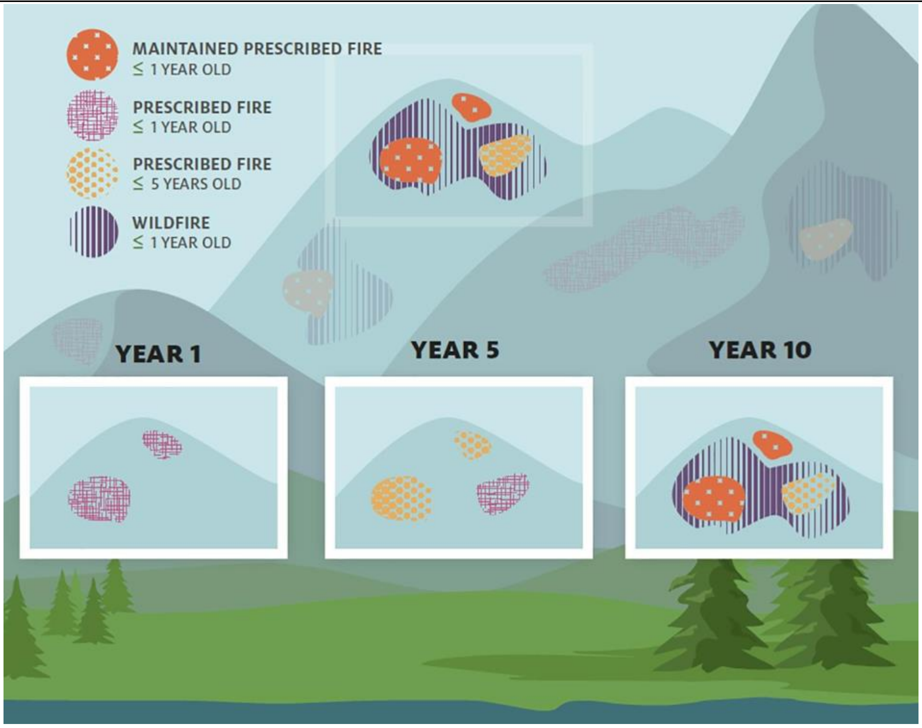
The smoke emissions and corresponding modeling of air quality impacts (CHAPTER 5) represent the key inputs to the quantitative analyses that form the backbone of this assessment. The results of the air quality modeling directly inform both human and ecosystem exposure with only the resulting human health impacts being quantitatively examined. However, this assessment also provides a qualitative discussion of both health and ecosystem impacts attributed to smoke exposure (CHAPTER 6). The current understanding of the health effects of wildland fire smoke exposure, as well as ambient $PM_{2.5}$ and ozone exposure, are subsequently used within BenMAP–CE to quantify the number of deaths and illnesses attributed to smoke from the different scenarios examined within both case studies.

Additionally, scientific evidence supports the availability and efficacy of various actions and interventions that can be employed at the individual and community level to mitigate the public health impact of smoke exposure (CHAPTER 6). The overall population $PM_{2.5}$ exposure reductions estimated from these actions and interventions allows for a limited quantitative assessment of the potential public health implications of promoting such measures (CHAPTER 8). Although these actions and interventions can be instituted for both wildfires and prescribed fires, the planned nature of prescribed fires enhances opportunities for public engagement surrounding prescribed fires, and increases the opportunities to inform populations at risk of wildfire smoke-related health effects of actions they can take to protect themselves. In addition to the quantitative and qualitative discussions that directly support components of the conceptual framework, this assessment also presents an overview of the current state of air quality monitoring for wildland fire smoke. Although the discussion of air quality monitoring does not represent a defined component of the conceptual framework, it is important to consider in the process of interpreting both the air quality modeling output and epidemiologic studies examining the health effects of smoke, which are the key inputs to the estimation of health impacts.

### 9.3.2 Overarching Limitations

As thoroughly detailed in CHAPTER 2, and noted in the previous section, the overall conceptual framework for conducting this assessment identifies numerous factors to consider in examining trade-offs between different fire management strategies, including prescribed fire, and the resulting effects, both positive and negative. While many of these factors are characterized within this assessment, there are spatial and temporal dimensions of fire management strategies that are not addressed. In addition, this assessment does not assess the effect of fire management strategies on the probability of wildfire occurrence (i.e., ignition probability), which is potentially a key factor in assessing differences in the cumulative effects of those strategies as depicted in Equation 2-1 in CHAPTER 2. As recently discussed in Hunter and Robles (2020), the comparison of positive and negative effects of prescribed fire and wildfire is not a static comparison, but one that should be conducted by considering the spatial and temporal aspect of prescribed fires and their interaction with the likelihood, severity, and magnitude of wildfire over a specific time horizon.

In comparison to wildfires, which occur at one uncertain point in time, but can vary in length from a few days to months, prescribed fires occur at planned times episodically over many years. Prescribed fires are conducted to achieve a resource benefit (see CHAPTER 3), with one of the overarching assumptions being that the prescribed fire will contribute to reducing the effect (e.g., size and severity) of a future wildfire. However, to achieve this desired outcome requires a series of prescribed fires over time that provide a patchwork of areas with less fuel, not an individual fire on its own, to minimize the risk of a severe, catastrophic wildfire occurring within the vicinity of the prescribed fires (see Figure 9-5).




Source: Hunter and Robles (2020), copyright permission pending.

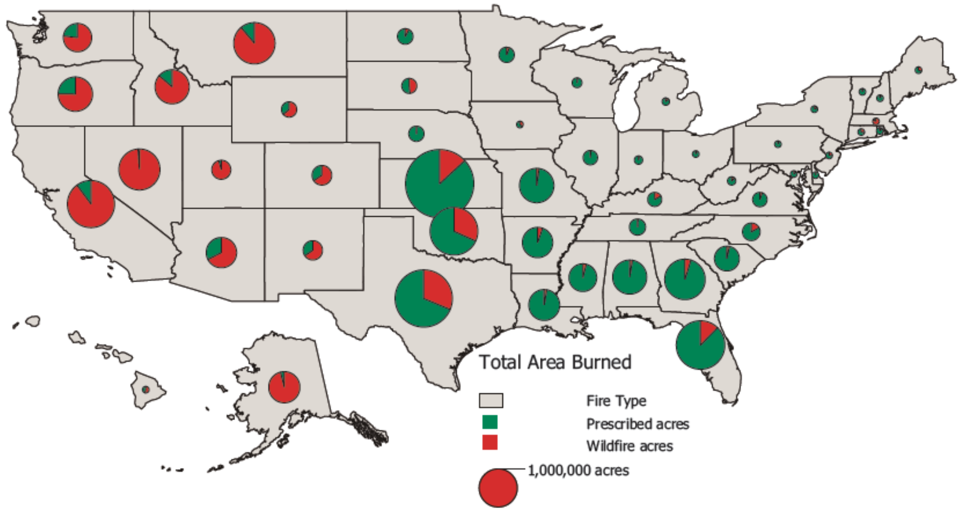
**Figure 9-5 Conceptual diagram presented by Hunter and Robles (2020) for assessing the impacts of prescribed fire compared to wildfire.**

Fully accounting for the trade-offs of smoke impacts between prescribed fire and a wildfire requires an understanding of the intersection of prescribed fire activity (both the total number of prescribed fires and the frequency of prescribed fires) with a wildfire. While over a long enough time period, the probability that a specific location will experience a wildfire can be substantial, there is still uncertainty as to when that fire would occur and how severe it would be. Therefore, although prescribed fires may reduce both the ignition probabilities and the severity of fires, they produce smoke that may, or may not, have occurred due to a potential future wildfire. Focusing the analyses conducted within this assessment around two previous wildfires and the land management strategies associated with each, did not allow for the consideration of ignition probabilities along with the total number and frequency of prescribed fires required to minimize the effects of a wildfire. Instead, these case studies address hypothetical scenarios by asking how the effects of fires that did occur might have differed under different types of fire management strategies. The information provided by these case studies is informative in assessing the benefits of different fire management strategies given the occurrence of fire, but does not address the uncertainty in the time horizon for fire in the landscape, nor the cumulative effects on health of a series of prescribed fire activities.

Although for the TC6 Fire case study, there was some information on prescribed fire activity over time, the time window over which these fires occurred complicated the ability to conduct a direct comparison of smoke impacts between prescribed fire and wildfire. As a result, for the TC6 Fire case study, it is assumed that all prescribed fire activity, and subsequent smoke exposures, occurred at one point in time (i.e., September 2019). For the Rough Fire case study the examination of prescribed fire activity is purely hypothetical, as there was no actual prescribed fire activity in the vicinity of the fire. However, by modeling the proposed Boulder Creek Prescribed Fire as if it actually occurred does provide some indication of the potential impact of a prescribed fire on reducing the size of the actual Rough Fire. Therefore, for both case studies, exposure to prescribed fire smoke is being treated as a static event and not the episodic event it is in actuality.

The treatment of prescribed fires as events occuring at one point in time within this assessment, out of both analytical convenience and sparseness of available data, also has ramifications from a health perspective. The removal of the spatial and temporal pattern of prescribed fire activity does not allow for the analyses conducted to consider that the location of prescribed fires varies on a year-to-year basis. By excluding this variability in prescribed fire activity, it is not possible to account for the corresponding spatial and temporal variability in population exposures to smoke that would occur, which could potentially result in a different pattern of health impacts.

In addition to recognizing the spatial and temporal aspects of prescribed fires and wildfires, it is also imperative to highlight the vastly different landscapes, in terms of both ecosystem composition (e.g., forests vs. prairie) and the percent contribution of prescribed fire to total wildland fire activity across the U.S. (Figure 9-6). The regional variability in the number of acres burned by prescribed fire and wildfire nationally, specifically in areas with a higher percentage of prescribed fires such as the Southeast, is an additional important consideration when examining air quality impacts associated with different fire management strategies. The variability in the composition of fire activity nationally, clearly depicts why the results of the case study analyses are not easily transferrable to other parts of the country, especially to areas where the number of acres burned is dominated by prescribed fires. Lastly, as noted earlier in this section, the relationship between prescribed fires and wildfire ignition probabilities are unknown in the case study areas and it is unclear how this relationship varies nationally, particularly in locations dominated by prescribed fires.




Source: Baker et al. (2020), copyright permission pending.

**Figure 9-6 Acres burned by wildfire (red) and prescribed fire (green) in the U.S. in 2017.**

### 9.3.3 Identified Data Gaps and Uncertainties

In the process of developing the preceding chapters of this assessment, as well as the development of the main modeling framework for the air quality and health impact analyses, gaps were identified in the current scientific understanding of wildland fire smoke. Future efforts to collect data and conduct studies to fill in these gaps could aid in future assessments and allow for a more extensive quantitative estimation of impacts and trade-offs between prescribed fire and wildfire.

A main overarching data gap that filters into multiple aspects of this assessment, but does not represent a key component of the conceptual framework, is the availability of ground-level air quality monitoring data for wildfire smoke. The challenges associated with monitoring wildfire smoke (see Section 4.5), and the resulting paucity of monitoring data, represents an important data gap because air quality monitoring data is instrumental in the assessment of health effects through epidemiologic studies as well as in air quality modeling to validate model predictions.

Even without a dense monitoring network to more fully capture the temporal and spatial patterns of population-level exposures to wildfire smoke, epidemiologic studies have still been able to use available air quality data (e.g., satellite, modeling, etc.) to assess the health effects of wildfire smoke. While these studies have been extremely informative and valuable to build upon the broad understanding of the health effects of ambient exposures to $PM_{2.5}$ and ozone, uncertainties remain with respect to both exposure assessment as well as a broader understanding of the health implications of exposures to different durations of wildland fire smoke (e.g., repeated peak exposures over many days, exposures over multiple fire seasons). Additionally, as reflected in the sensitivity analysis conducted in CHAPTER 8 (Section 8.3.2), additional epidemiologic studies that more fully capture wildfire smoke exposure can help inform the concentration-response (C-R) relationship to better understand if there are differences compared to the C-R relationship for ambient $PM_{2.5}$ exposures that should be considered when examining the public health impacts of smoke based on different fire management strategies. In addition, better understanding of the differences in the composition of smoke resulting from different burn conditions (e.g., fuel characteristics, moisture levels, and the health effects associated with different smoke composition) can help improve the ability to differentiate between fire management strategies with and without prescribed fire, and also strategies for designing prescribed fire programs to minimize negative health impacts.

In considering the approach used within this assessment for the air quality modeling, the assumptions that factored into the methods employed recognize the same overarching limitations discussed in Section 9.3.2 (see Section 5.4). As noted earlier within this chapter, expert judgment was relied upon heavily in the defining of the hypothetical scenarios for each of the case studies. In addition, in the modeling of prescribed fires for both case studies, all prescribed fire activity over many years was modeled for 1 month in the instance of the TC6 Fire case study or there was no prescribed fire activity in the case of the Rough Fire case study, resulting on the reliance of a proposed prescribed fire that never occurred. Results of analyses, such as those conducted within this assessment, could more fully capture the differences between different land management and fire management strategies through data that can capture the temporal and spatial scale of prescribed fire activity. Although a fuller accounting of prescribed fire activity over time and space is a key data gap, it also remains unclear how prescribed fire activity could impact the size and duration of a wildfire. The relationship between prescribed fire activity and its influence on wildfire size and duration, especially for larger fires (e.g., Rough Fire) represents a key area that requires additional exploration and prevents extrapolation of results from these case studies to other parts of the U.S.

In addition to the data gaps identified within this section, there are numerous ancillary issues associated with wildfires that are not addressed within this assessment, but this does not diminish their importance. For example, it is recognized that wildfires can lead to the resuspension of legacy pollutants, such as asbestos, lead, and mercury. These pollutants have been shown to lead to a range of health effects, but it remains unclear how much wildfires contribute to population-level exposures to these pollutants. Additionally, over time the wildland–urban interface (WUI) has expanded rapidly in many parts of the U.S. (Radeloff et al., 2018). This expansion of the WUI has resulted in substantial portions of the population now residing in locations that are considered high-fire-risk areas. The growth of the WUI not only increases the risk of fire ignitions, but also direct fire effects. Although CHAPTER 7 broadly captures direct fire effects, including those associated with the burning of structures that could be experienced within the WUI, currently available information is not conducive to providing location-specific estimates of the costs of wildfire. Lastly, as wildfires infringe upon the WUI it can lead to a change in the composition of smoke as homes and structures are burned and the likelihood of populations being exposed to wildfire smoke.

## 9.4 Key Insights from Case Study Analyses

This assessment and the accompanying quantitative analyses, represent an incremental advancement in the understanding of the air quality and health impacts of wildland fires under different fire management strategies. As a reminder, the results of the analyses conducted within this assessment are specific to the case study areas and are not intended to represent the air quality and health impacts that would be observed in other locations around the U.S. The case studies were chosen to illustrate the type and nature of air quality and health impacts associated with different fire management strategies. Additionally, within this assessment it is important to reiterate that in examining the air quality and health impacts attributed to prescribed fires, the analyses are retrospective and represent locations that experienced a wildfire, and therefore, do not (1) account for the temporal and spatial variability of prescribed fires occurring over many years that happens in reality or would happen in an ideal situation to minimize the risk of catastrophic wildfire and (2) incorporate an estimate of uncertainty to account for the probability that a wildfire may not occur in a location where there was prescribed fire activity. The case study analyses conducted within this assessment support the following observations:

- To provide a reasonable estimation of air quality and health impacts from wildland fire, location-specific information on fuels is needed to support air quality modeling.
- Smoke impacts on health are dependent upon population proximity to wildland fire events.
- Predicted concentrations of $PM_{2.5}$ from prescribed fires are smaller in magnitude and shorter in duration, and the estimated aggregate population exposure is smaller than for each hypothetical scenario and the actual fires in both case studies.
    - The smaller estimated aggregate population PM2.5 exposures for prescribed fires in both case studies can be attributed to the small spatial extent of each prescribed fire and the meteorological characteristics of the days in which the prescribed fires occurred.
    - Although prescribed fires are timed for days with specific meterological conditions to reduce population exposures to smoke, analyses show that air quality and public health impacts are still observable.
- Within the case study areas, ozone produced from wildland fires is shown to have less impacts on air quality and public health, providing additional support to the current public health focus being on reducing exposures to $PM_{2.5}$.
- Wildfires that are short in duration and size and not near large population centers, such as the TC6 Fire, can still result in public health impacts, albeit substantially smaller than larger wildfires, such as Rough Fire.

- Wildfires that yield positive resource benefits on their own (i.e., Sheep Complex Fire) could be more effective in reducing future air quality and public health impacts when used in combination with prescribed fires (i.e., Boulder Creek Prescribed Fire).
    - Well designed prescribed fires targeted for specific locations, such as the proposed Boulder Creek Prescribed Fire, along with the prescribed fires around the TC6 Fire, can potentially reduce the size and resulting air quality and public health impacts of future wildfires.
- Communicating the benefits of actions and interventions that reduce or mitigate $PM_{2.5}$ exposures can contribute to reducing the public health impacts attributed to wildland fire smoke if these actions are more widely used by the population.

## 9.5 Future Directions

The analyses conducted within this assessment lay the foundation for future research efforts to examine the air quality and corresponding public health impacts of smoke from wildland fire under different fire management strategies. While the results of the quantitative analyses provide initial evidence of differences in smoke impacts between prescribed fire and wildfire, additional research efforts that attempt to address the following issues will further enhance the applicability of future analyses examining the trade-offs between different fire management strategies:

- Identification and development of methods to account for the temporal (i.e., frequency) and spatial component of prescribed fires and their relationship with wildfires. Related to this advancement would include gaining a better understanding of how to capture the health effects of repeated exposure to smoke from prescribed fires over many years and how that compares to the health effects experienced during singular wildfire events.
- Enhanced characterization of the relationship between prescribed fire and wildfire on the landscape. This would include analyses that examine specific spatial domains with prescribed fires and the number of those locations that also experienced a wildfire, along with identifying whether prescribed fires were able to reduce characteristics of the wildfire (e.g., size, intensity, duration, etc.). This advancement would then allow for a greater understanding of the costs and benefits of different fire management strategies with and without wildfire.
- Analyses that characterize the role of topography and meteorology, in combination with the frequency of prescribed fires within a spatial domain, on the potential for population centers to experience smoke impacts from wildland fires.
- Characterization of how air quality impacts differ between prescribed fire and wildfire in different parts of the U.S., specifically in locations where prescribed fire is the dominant wildland fire activity, to gain a better understanding of the ability to extrapolate results across geographic locations.
- Centralized repository to capture prescribed fire data to enhance future assessments using more recent data. Such a repository would include, but not be limited to, information on location, timing (dates and approximate start and end time), actual acres burned, fuel type and loading information, and any air quality monitoring data collected.

In addition to these broad areas that require additional research to support future analyses, there are overarching uncertainties and limitations identified in previous chapters that could further enhance our understanding of the overall impacts of wildland fire smoke. These areas of additional research include enhanced air quality monitoring capabilities for wildfire smoke, better characterization of wildland fire smoke exposures for health studies, additional understanding of the health effects of wildfire smoke over many seasons, and a fuller accounting for the role of public health actions and interventions in reducing or mitigating wildland fire smoke exposure. Collectively, these broader research initiatives in combination with those areas this assessment was unable to account for, noted within this section, would allow for a fuller characterization of the air quality and health impacts due to different fire management strategies.

## 9.6 References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# APPENDIX

## A.1. SUPPLEMENTAL INFORMATION FOR CHAPTER 1

No supplemental information.

## A.2. SUPPLEMENTAL INFORMATION FOR CHAPTER 2

Table A.2-1 represents a more detailed version of Table 2-1 that attempts to characterize whether the impacts associated with wildland fire are negative or positive.

**Table A.2-1 Positive and negative impacts associated with Wildland Fire[a].**

| Categories | Prescribed Fire: During the Event | Prescribed Fire: Post-Event[b] | Wildfire: During the Event | Wildfire: Post-Event |
|---|---|---|---|---|
| *Firefighting* | | | | |
| Firefighter safety | − | + | − | + and/or − |
| Firefighter injuries/fatalities | − | + | − | + and/or − |
| Firefighter health, both mental and physical (mental and physical) | − | + | − | + and/or − |
| *Economic* | | | | |
| Evacuations | NV | + | − | + and/or − |
| Property (e.g., structures) | NV | + | − | + and/or − |
| Property (e.g., loss of ecosystem services) | + and/or − | + | − | + and/or − |
| Timber and grazing | + and/or − | + | − | + and/or − |
| Infrastructure (e.g., powerlines, recreation, others) | NV | + | − | + and/or − |
| Municipal watersheds (e.g., reservoirs, industry, agriculture, drinking) | + | + | − | + and/or − |
| Tourism (e.g., recreation, lodging, restaurants, etc.) | + and/or − | + | − | + and/or − |
| Aesthetics (e.g., property value, view shed, etc,) | + and/or − | + | − | + and/or − |

## Table A.2-1 (Continued): Positive and Negative Impacts Associated with Wildland Fire.[a]

| Categories | Prescribed Fire: During the Event | Prescribed Fire: Post-Event[b] | Wildfire: During the Event | Wildfire: Post-Event |
|---|---|---|---|---|
| Natural and cultural resources | + and/or − | + | − | + and/or − |
| Fuel reduction—cost effective method of treating acres | NV | + | + and/or − | + and/or − |
| Fuel reduction—treatment opportunities not limited to markets | NV | + | + and/or − | + and/or − |
| *Ecological* | | | | |
| Ecological services including game and endangered species | NV | + | + and/or − | + and/or − |
| Ecosystem health and resiliency | NV | + | + and/or − | + and/or − |
| Restoration/maintenance of historic natural fire regime | NV | + | + and/or − | + and/or − |
| Invasive species | + and/or – or NV | + | + and/or − | + and/or − |
| Climate change (e.g., GHG, carbon) | + and/or − | + and/or − | + and/or − | + and/or − |
| Redistribution of toxics and nutrients (e.g., mercury, metals, sulfur, nitrogen) | −(?) | −(?) | −(?) | −(?) |
| Soil and water quality and quantity | + and/or − | + and/or − | + and/or − | + and/or − |
| *Public Health: Direct Fire* | | | | |
| Injuries | NV | + | − | + and/or − |
| Hospitalizations | NV | + | − | + and/or − |
| Premature mortality | NV | + | − | + and/or − |
| *Public Health: Air Quality* | | | | |
| Hospitalizations and emergency department visits | − | + | − | + and/or − |
| Premature mortality | − | + | − | + and/or − |
| Nonfatal heart attacks/cerebrovascular events | − | + | − | + and/or − |
| Asthma effects | − | + | − | + and/or − |
| Other respiratory and illness effects | − | + | − | + and/or − |

**Table A.2-1 (Continued): Positive and Negative Impacts Associated with Wildland Fire.[a]**

| Categories | Prescribed Fire: During the Event | Prescribed Fire: Post-Event[b] | Wildfire: During the Event | Wildfire: Post-Event |
|---|---|---|---|---|
| Loss of work and school days | − | + | − | + and/or − |

GHG = greenhouse gas; NV = not available.

Note: Positive (+): providing some advantage (e.g., restoring ecosystems, mitigating the risk or loss from a wildfire, etc.). Negative (−): negative consequences from a fire (e.g., property or infrastructure damage or loss).

[a]Signs on the impact categories are based on literature discussed throughout this report as well as expert judgements from the report authors.

[b]Post-event includes impacts expected to occur as a result of reductions in the risk of more severe and damaging wildfires. For example, reduced risk of severe wildfires reduces risks to firefighters, and reduces risks of poor air quality and related health effects. Thus, a positive sign on the post-fire effects of prescribed fires on health categories does not indicate the fire itself improves health, but rather than the reduction in risk of severe wildfires improves future public health.

[c]For many of the categories with an NA for prescribed fires, the impact will not be applicable as long as the prescribed fire remains consistent with the management objectives. In the rare cases where prescribed fires are no longer meeting their objectives, they can be reclassified as wildfires and will in those cases have the potential for additional negative impacts.

## A.3. SUPPLEMENTAL INFORMATION FOR CHAPTER 3

No supplemental information.

## A.4. SUPPLEMENTAL INFORMATION FOR CHAPTER 4

**Table A.4-1 Criteria gas pollutant Federal Reference Methods (FRMs) and most widely employed Federal Equivalent Methods (FEMs) used in U.S. EPA regulatory monitoring.**

| Pollutant Method | Operating Principle | FRM Regulatory Citation | Notes |
|---|---|---|---|
| *CO* | | | |
| Automated FRM | NDIR | 40 CFR Part 50 Appendix C (U.S. EPA, 2020a) | --- |
| Automated FEM | Mercury replacement UV photometry | --- | Only existing CO FEM. |
| *$O_3$* | | | |
| Automated FRM | Chemiluminescence | 40 CFR Part 50 Appendix D (U.S. EPA, 2011b) | Employs chemiluminescence reaction between ozone and ethylene of NO. Ethylene chemiluminescence FRM instruments no longer commercially available. NO chemiluminescence method promulgated as a new FRM in 2015. NO chemiluminescence FRM instruments available commercially. |
| Automated FEM | UV Photometry | --- | Severe smoke interference resulting in overestimation of ozone concentrations (Long et al., In Press). |
| Automated FEM | Open-path DOAS | --- | Employs open monitoring path length between 20−1,000 m |
| *$NO_2$* | | | |
| Automated FRM | Chemiluminescence | 40 CFR Part 50 Appendix F (U.S. EPA, 2011a) | Employs the catalytic conversion of $NO_2$ to NO with subsequent chemiluminescence detection of the reaction between NO and $O_3$. Known interference by higher oxides of nitrogen (e.g., $HNO_3$, $HNO_2$, particulate nitrate). |

**Table A.4-1 (Continued): Criteria gas pollutant Federal Reference Methods (FRMs) and most widely employed Federal Equivalent Methods (FEMs) used in U.S. EPA regulatory monitoring.**

| Pollutant Method | Operating Principle | FRM Regulatory Citation | Notes |
|---|---|---|---|
| Automated FEM | Chemiluminescence | --- | Employs the photolytic conversion of $NO_2$ to NO with subsequent chemiluminescence detection of the reaction between NO and $O_3$. Considered more specific for $NO_2$ than the FRM and is a candidate for future FRM consideration. |
| Automated FEM | Spectroscopic | --- | Employs methods such as CAPS spectrometry. |
| Automated FEM | Open-path DOAS | --- | Employs open monitoring path length between 50−1,000 m |
| *$SO_2$* | | | |
| Automated FRM | UV fluorescence | 40 CFR Part 50 Appendix A-1 (U.S. EPA, 2011c) | Previously an FEM, promulgated as a new FRM in 2010. |
| Manual FRM | Pararosaniline method | 40 CFR Part 50 Appendix A-2 (U.S. EPA, 2020b) | Manual wet chemical method not used at present time. |
| Automated FEM | UV fluorescence | --- | Promulgated as a new FRM in 2010. |
| Automated FEM | Open-path DOAS | --- | Employs open monitoring path length between 20−1,000 m. |

CAPS = cavity attenuated phase shift ; CFR = Code of Federal Regulations; CO = carbon monoxide; DOAS = differential optical absorption spectroscopy; FEM = Federal Equivalent Method; FRM = Federal Reference Method; $HNO_2$ = nitrous acid; $HNO_3$ = nitric acid; NDIR = nondispersive infrared photometry; NO = nitric oxide; $NO_2$ = nitrogen dioxide; $O_3$ = ozone; $SO_2$ = sulfur dioxide; UV = ultraviolet.

**Table A.4-2 Summary of low-cost sensors evaluated in biomass smoke.**

| Vendor | Model | Study Type | Max $PM_{2.5}$ | Reference | Reference Regression Slope | Citation |
|---|---|---|---|---|---|---|
| Aeroqual | AQY 1 | Field | ~300 (μg/m$^3$) | FEM/nonFEM | 0.54−2.18 | Holder et al. (2020) |
| eLichens | IAQPS | Field | ~150 (μg/m$^3$) | Multiple FEMs | ~0.45−0.80 | Delp and Singer (2020) |
| Purple Air | PA-II-SD | Field | ~300 (μg/m$^3$) | FEM/nonFEM | 0.93−1.61 | Holder et al. (2020) |
| Purple Air | PA-II | Field | 33 (μg/m$^3$)‡ | FEM | 0.43 | Mehadi et al. (2019) |
| Purple Air | PA-II | Field | ~150 (μg/m$^3$) | Multiple FEMs | 0.39−0.54 | Delp and Singer (2020) |
| Sensit | RAMP | Field | ~300 (μg/m$^3$) | FEM/nonFEM | 0.77−1.48 | Holder et al. (2020) |
| Sensit | RAMP | Chamber | ~1,800 (μg/m$^3$) | FRM | 1.35−2.43 | Landis et al. (2021) |
| Thingy | Thingy AQ | Chamber | ~1,800 (μg/m$^3$) | FRM | 2.14−4.95 | Landis et al. (2021) |
| Wicked Device | Air Quality Egg | Field | ~150 (μg/m$^3$) | Multiple FEMs | ~0.32−0.65 | Delp and Singer (2020) |

FEM = Federal Equivalent Method; FRM = Federal Reference Method.

‡ Daily average concentration.

## Table A.4-3 Summary of routine $PM_{2.5}$ measurement methods and data availability.

| Methods | $PM_{2.5}$ FRMs | CSN and IMPROVE | $PM_{2.5}$ Continuous FEMs | Other $PM_{2.5}$ Continuous Methods | Sensor Networks |
|---|---|---|---|---|---|
| *Method Specifications:* | | | | | |
| Manual or automated | Manual | Manual | Automated continuous | Automated continuous | Automated continuous |
| Measurement principle(s) | Gravimetric in laboratory | Ion chromotography, x-ray fluorescence, Thermal Optical Reflectance all in laboratory | Key ones include: β attenuation, TEOM, and LED broadband spectroscopy | Key ones include: β Attenuation, Nephelometers, and TEOMs | Optical PM sensors |
| Method or manufacturer-reported concentration range | 0−200 µg/$m^3$ however, in AQS there are a few values in the Hazardous AQI category | 0−200 µg/$m^3$ | BAM-Range: 0−1,000 µg/$m^3$ standard; up to 10,000 µg/$m^3$; T640-Range: 0.1−10,000 µg/$m^3$ | | Purple Air with U.S. EPA-ORD correction equation (Barkjohn et al., 2020)<br>0−250 µg/$m^3$ range (>250 µg/$m^3$ may underestimate true $PM_{2.5}$) |
| Manufacturer-reported data resolution | 0.1 µg/$^3$ | 0.1 µg/$m^3$ | M1 BAM: 1 µg/$m^3$<br>TEOM and T640: 0.1 µg/$m^{-3}$ | | 0.1 µg/$m^3$ |
| *Data Attributes of Each Method:* | | | | | |
| Data availability (typical) | ~1−3 mo after sample collection | ~3−6 mo after sample collection | Hourly data are usually posted to AIRNow within several minutes past the end of the hour | | Near real time on Purple Air web site<br>Hourly update on AIRNow fire and smoke map |

**Table A.4-3 (Continued): Summary of routine $PM_{2.5}$ measurement methods and data availability.**

| Methods | $PM_{2.5}$ FRMs | CSN and IMPROVE | $PM_{2.5}$ Continuous FEMs | Other $PM_{2.5}$ Continuous Methods | Sensor Networks |
|---|---|---|---|---|---|
| Data interval available | 24-h midnight to midnight local standard time. Some sites operate daily, others every 3rd or 6th day, some QA samplers every 12th day | 24-h midnight to midnight local standard time. Most sites operate every 3rd day; some CSN sites every 6th day | Hourly data is collected and reported by AIRNow; some methods have subhourly data available<br>(T640 has 1-min data available—smoothed in rolling 10-min averages) | | Sub hourly; data layer on AIRNow fire page is hourly |
| Where are data available? | AQS—https://www.epa.gov/aqs/obtaining-aqs-data | AQS and UC Davis web site—https://airquality.ucdavis.edu/csn<br>https://airquality.ucdavis.edu/improve | AQS, AIRNow, AIRNowTech, and many State and local web sites—https://www.airnow.gov/<br>http://airnowtech.org/<br>(credentials required) | | Purple air web site, AIRNow fire and smoke page—https://fire.airnow.gov/<br>https://www.purpleair.com |
| Highest concentrations reported with this method to AQS (2010−2019). | There are seven cases in the "Hazardous AQI category" all in AK, CA, or OR. The highest reported concentration was 411.7 µg/$m^3$. | There are no cases in Hazardous AQI category. There are 13 cases in the "very unhealthy" AQI category. 8 by the IMPROVE method; high = 210.2 µg/$m^3$ all in CA and MT; 1 by a SASS (CSN) at 206.7 µg/$m^3$ in IL; and 4 cases listed as a generic filter-based method, high = 230 µg/$m^3$ all in CA and NV. | Six cases reported in the Hazardous AQI category. All with a BAM in CA, MT, or WA. High = 557.1 µg/$m^3$. | In the Hazardous AQI category there are 21 cases with a Correlated Nephelometer all in OR or WA, high reported = 570.3 µg/$m^3$; 34 cases with a BAM all reported in AK, CA, ID, or MT, high = 642.0 µg/$m^3$; 1 case with a TEOM at 252.0 µg/$m^3$ in ID. | NA |
| *Network Attributes:* | | | | | |
| U.S. Stations Reporting to AQS (2020) | 678 | CSN = 143<br>IMPROVE = 156 | 678 | 305 | NA |

## Table A.4-3 (Continued): Summary of routine $PM_{2.5}$ measurement methods and data availability.

| Methods | $PM_{2.5}$ FRMs | CSN and IMPROVE | $PM_{2.5}$ Continuous FEMs | Other $PM_{2.5}$ Continuous Methods | Sensor Networks |
|---|---|---|---|---|---|
| Key network Design features | Most sites are population-orientated locations in CBSA's. Each state should have a background and transport site | CSN includes STN, Ncore, and supplemental sites (most in CBSAs.) IMPROVE supports regional haze program with most sites in Class 1 areas and national parks. Some IMPROVE protocol sites are operated in lieu of CSN. | Same as FRM | Same as FRM. In WA and OR nephelometers are often used to supplement AQI reporting in communicates where NAAQS comparable data are not required; however, smoke impacts may be of concern. | Sites may exist anywhere users report via internet to Purple Air site. Users self-describe if ambient air or inside. Note: only sites described as ambient air are used in fire and smoke map layer. |

AQI = Air Quality Index; AQS = Air Quality System; CBSA = core-based statistical area; CSN = Chemical Speciation Network; IMPROVE = Interagency Monitoring of Protected Visual Environments; LED = light-emitting diode; h = hour; min = minute; mo= month; NCore = National Core Network; ORD = Office of Research and Development; $PM_{2.5}$= particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; QA = quality assurance; STN = Speciation Trends Network; TEOM = Tapered Element Oscillating Microbalance.

**Table A.4-4 Overview of wildland fire relevant imagery/composition satellite data products.**

| | | System Content | | | | | |
|---|---|---|---|---|---|---|---|
| **Satellite Product** | **Instrument** | **NOAA Aerosol Watch** | **NOAA JSTAR Mapper** | **NOAA Hazard Mapping System** | **NASA LANCE/World View** | **U.S. EPA AirNow Tech** | **U.S. EPA Remote Sensing Information Gateway** |
| Corrected Reflectance True Color | GOES ABI | I | | I, D | | | |
| | VIIRS | I | I | I, D | I, D | | I, D |
| | MODIS | | | | I, D | I | I, D |
| Digitized Smoke Analysis | ABI + VIIRS | | | I, D | | | |
| Aerosol Optical Depth | ABI | I | | | | | |
| | VIIRS | I | I | | I, D | | I, D |
| | MODIS | | | | I, D | | I, D |
| Aerosol Detection (smoke/dust) | ABI | I | | | | I | |
| | VIIRS | I | I | | I, D | | |

**Table A.4-4 (Continued): Overview of wildland fire relevant imagery/composition satellite data products.**

| | | System Content | | | | | |
|---|---|---|---|---|---|---|---|
| **Satellite Product** | **Instrument** | **NOAA Aerosol Watch** | **NOAA JSTAR Mapper** | **NOAA Hazard Mapping System** | **NASA LANCE/World View** | **U.S. EPA AirNow Tech** | **U.S. EPA Remote Sensing Information Gateway** |
| Fire Characterization/Hot Spots/Active Fires | ABI | I | | | I, D | | I, D |
| | VIIRS | I | I | | I, D | | I, D |
| AI | TROPOMI | | I | | I, D | | I, D |
| CO | | | | | | | |
| $NO_2$ | | | | | | | |
| Satellite predicted $PM_{2.5}$ | | I, D | | | | I, D (ASDP) | |
| Surface concentration measurements from AirNow or AQS ($PM_{2.5}$, $O_3$, $NO_2$, $SO_2$) | AirNow | I (h $PM_{2.5}$ only) | | | | I,D | I,D |
| | AQS | | | | | I,D | I,D |

ABI = Advanced Baseline Imager; AI = aerosol index; AQS = Air Quality System; CO = carbon monoxide; D = data available; GOES = Geostationary Operational Environmental Satellite; I = image available; MODIS = Moderate Resolution Imaging Spectroradiometer; NASA = National Aeronautics and Space Administration; $NO_2$ = nitrogen dioxide; NOAA = National Oceanic and Atmospheric Administration; $O_3$ = ozone; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm, $SO_2$ = sulfur dioxide; VIIRS = Visual Infrared Imaging Radiometer Suite.

## Table A.4-5 Ground-based remote sensing networks vertical (profile and total column data).

| Network and/or Instrument | Lead Organization | Total Number of Sites in U.S. | Date Latency | Initiated Measurement | Relevant Constituent/ Properties | URL for Information on measurements/data |
|---|---|---|---|---|---|---|
| Automated Surface Observing System (ASOS)/ | NOAA | 900 | | | Surface visibility | https://www.aviationweather.gov/metar?gis=off |
| Photochemical Assessment Monitoring Stations | U.S. EPA | ~40 | | 2021 | Backscatter aerosol profiles (15 km), PBLH, aerosol layer identification | https://alg.umbc.edu/ucn |
| MPLNET—Micro-pulse LiDAR Network | NASA (federated) | 35 | | 2000 | Aerosols and cloud layer heights | http://mplnet.gsfc.nasa.gov/ |
| AErosol RObotic NETwork (AERONET) | NASA (federated) | ~100 | | 1998 | Aerosol spectral optical depths, aerosol size distributions, and precipitable water | http://aeronet.gsfc.nasa.gov/index.html |
| Pandonia Global Network | NASA-ESA | 14 | | | Total Column $O_3$, $NO_2$, Tropospheric Column $NO_2$, HCHO, and Surface $NO_2$ | https://www.pandonia-global-network.org/ |

ESA = European Space Agency; HCHO = formaldehyde; LiDAR = Light Detection and Ranging; MPLENT = micro-pulse LiDAR; NASA = National Aeronautics and Space Administration; NOAA = National Oceanic and Atmospheric Administration; $NO_2$ = nitrogen dioxide; $O_3$ = ozone; PBLH = planetary boundary layer heights.

### A.4.1. Example State and Local Sponsored Smoke Blogs

Information on general ambient air quality, the impact of wildland fire smoke on current ambient air quality conditions, and air quality forecasts are available to the public through the multiagency AirNow website as well as state and local websites. Several western states maintain websites ("smoke blogs") dedicated to providing the public with information on wildfire smoke impacts (Examples listed below). The material delivered by these smoke blogs varies from state to state with the sites leveraging smoke and fire observations and forecast products from a variety of sources (e.g., AirNow, dedicated state/local monitors). Below are some example state and local websites and smoke blogs that provide air quality information to the public and are a resource during wildfire events with the landing page title in parentheses.

- Alaska
  (Wildfire Smoke—Particulate Matter Information)
  https://dec.alaska.gov/air/air-monitoring/wildfire-smoke-info/
- Arizona
  (Wildfire Support)
  http://www.azdeq.gov/node/2913
- California
  Butte County Air Quality Management District (AQMD, Wildfires and Air Quality)
  https://bcaqmd.org/resources-education/wildfires/
- North Coast Unified Air Quality Management District
  http://www.ncuaqmd.org/index.php?page=wildfire
- Santa Barbara Pollution Control District, California (Today's Air Quality and Forecasts)
  https://www.ourair.org/todays-air-quality/
- South Coast Air Quality Management District, California (South Coast AQMD)
  http://www.aqmd.gov/
- Ventura County Air Pollution Control District (VCAPD)
  http://www.vcapcd.org/
- Idaho
  (Air Quality Index [AQI])
  https://www.deq.idaho.gov/air-quality/air-quality-index/
- (Idaho Smoke Information)
  http://idsmoke.blogspot.com/
- Montana
  (Wildfire Smoke Update)
  http://svc.mt.gov/deq/todaysair/smokereport/mostrecentupdate.aspx
- (Montana Wildfire Smoke)
  https://www.montanawildfiresmoke.org/

- Nevada
  (Northern Sierra Air Quality Management District)
  https://myairdistrict.com/
- New Mexico
  (Wildfire and Prescribed Fire Smoke Resources)
  https://www.env.nm.gov/air-quality/fire-smoke-links/
- North Carolina
  (Air Quality)
  https://deq.nc.gov/about/divisions/air-quality
- Oregon
  (Oregon Smoke Information)
  http://oregonsmoke.blogspot.com/
- South Carolina
  (Wildfires—Protect Yourself)
  https://scdhec.gov/disaster-preparedness/wildfires-protect-yourself
- Washington
  (Washington Smoke Information)
  https://wasmoke.blogspot.com/

### A.4.2. U.S. EPA $PM_{2.5}$ Mass Monitoring

The particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm ($PM_{2.5}$) monitoring program is one of the major ambient air monitoring programs operated across the country. For most urban locations $PM_{2.5}$ monitors are sited at the neighborhood scale as defined in 40 Code of Federal Regulations (CFR) Appendix D to Part 58 (U.S. EPA, 2015), where $PM_{2.5}$ concentrations are reasonably homogeneous throughout an entire urban subregion. In each CBSA with a monitoring requirement, at least one $PM_{2.5}$ monitoring station representing area-wide air quality is to be sited in an area of expected maximum concentration.

There are three main components of the $PM_{2.5}$ monitoring program: 24-hour integrated filter-based Federal Reference Method (FRM) samplers, continuous Federal Equivalent Method (FEM) mass instrument measurements reported as 1-hour concentrations, and 24-hour integrated filter-based Chemical Speciation Network (CSN) samplers. The FRM data are primarily used for determining NAAQS compliance, but also serve other important purposes such as developing trends and evaluating the field performance FEM continuous mass instruments. Continuous FEM instrument data are also used for determining NAAQS compliance and their real-time data support public AQI communication and air quality forecasting on AirNow. FRMs have been available since the $PM_{2.5}$ monitoring network commenced operation in January of 1999, and $PM_{2.5}$ continuous FEMs became commercially available in 2008. Many State and local agencies are transitioning their regulatory $PM_{2.5}$ monitoring networks to continuous FEMs. However, even if a monitoring agency chooses to run $PM_{2.5}$ continuous FEMs at all their stations, some FRMs are still required. For example, FRMs are required under quality assurance requirements and at U.S. Environmental Protection Agency (U.S. EPA) National Core Network (NCore) Stations (Appendices A and D to 40 CFR Part 58) (U.S. EPA, 2019, 2015).

The CSN and related Interagency Monitoring of Protected Visual Environments (IMPROVE) network is used to provide chemical composition of the aerosol which serve a several objectives. The CSN program is managed by U.S. EPA with field operations conducted by state and local agencies and national contract laboratories responsible for shipping, handling, and analysis of samples. The IMPROVE is operated by the Department of the Interior (DOI) under the direction of a multiagency federal/state steering committee. The IMPROVE monitoring program supports the national goal of reducing haze to near natural levels in National Parks and wilderness areas.

In 2020 there were 678 FRM filter-based samplers included in the U.S. EPA $PM_{2.5}$ network that provide 24-hour $PM_{2.5}$ mass concentration data. Of these operating FRMs, 72 are providing daily $PM_{2.5}$ data, 320 every 3rd day, 229 every 6th day, and 57 every 12th day. As of 2020, there are 983 continuous $PM_{2.5}$ mass monitors that provide hourly data on a near real-time basis reporting across the country. A total of 678 of the $PM_{2.5}$ continuous monitors are FEMs and therefore used both for comparison with the NAAQS and to report the AQI. Another 305 monitors not approved as FEMs are operated primarily to report the AQI. These legacy $PM_{2.5}$ continuous monitors were largely purchased prior to the availability of designated $PM_{2.5}$ continuous FEMs instruments. The most widely used $PM_{2.5}$ continuous monitor not designated as an FEM is the Radiance Research (Seattle, WA) Model M903 nephelometer (locally correlated to an FRM).

The first designated automated $PM_{2.5}$ FEM instrument was the Met One Instruments (Grants Pass, OR) Model BAM 1020 (14C β attenuation radiometric method) in 2008. The BAM 1020 and more recently approved BAM 1022 account for approximately 50% and the Teledyne API (San Diego, CA) Model T640/T640x account for approximately 30% of the nationally operating automated $PM_{2.5}$ FEMs. The U.S. EPA has approved a total of 11 $PM_{2.5}$ automated methods as FEMs including beta attenuation from multiple instrument manufacturers; optical methods such as the GRIMM Aerosol Technik (Ainring, Germany) Model 180 and the Teledyne API Model T640/T640x; and methods employing the Thermo Environmental (Franklin, MA) Model 1405 Tapered Element Oscillating Microbalance (TEOM) with a Filter Dynamic Measurement System (FDMS).

### A.4.3. U.S. EPA $PM_{2.5}$ Speciation Monitoring

Particulate matter (PM) is the generic term for a broad class of chemically and physically diverse substances that exist as liquid and/or solid particles over a wide range of sizes. Particles originate from a variety of anthropogenic stationary and mobile sources, as well as from natural sources like wildfires. Particles may be emitted directly or formed in the atmosphere by photochemical transformations of gaseous precursors such as sulfur dioxide ($SO_2$), $NO_X$, ammonia ($NH_3$), and volatile organic compounds (VOCs). The chemical and physical properties of $PM_{2.5}$ vary greatly with time, region, meteorology, and source category. U.S. EPA implemented the CSN to investigate the chemical components of $PM_{2.5}$ at selected locations across the country. The CSN sample filters are analyzed for 33 trace elements using energy dispersive x-ray fluorescence [EDXRF; Watson et al. (1999); Jaklevic et al. (1981)], water soluble major ions (e.g., ammonium, potassium, nitrate, sulfate) using ion chromatography [IC; U.S. EPA (1999)], and elemental carbon (EC)/organic carbon (OC) using thermal optical reflectance [TOR; Chow et al. (1993); Huntzicker et al. (1982)]. Chemical composition can provide valuable information about the sources and relative toxicity of $PM_{2.5}$.

In 2020 the CSN continued routine long-term $PM_{2.5}$ measurements at 143 predominately urban locations. The major network components of the CSN include the Speciation Trends Network (STN), NCore stations, and supplemental speciation sites. STN sites are intended to be long-term locations where chemical section measurements are taken. NCore is a multipollutant network measuring $PM_{2.5}$ mass, criteria gases, and basic meteorology that has been in formal operation since January 1, 2011. Particle measurements made at NCore include $PM_{2.5}$ filter-based mass, which is largely the FRM, except in some rural locations that utilize the IMPROVE program $PM_{2.5}$ mass filter-based measurement; $PM_{2.5}$ speciation using either the CSN program or IMPROVE program; and coarse particulate matter ($PM_{10-2.5;}$ particulate matter with a nominal aerodynamic diameter less than or equal to 10 µm and greater than a nominal 2.5 µm) mass utilizing an FRM, FEM or IMPROVE samplers for some of the rural locations. As of 2020, the NCore network includes a total of 78 stations of which 63 are in urban or suburban stations designed to provide representative population exposure and another 15 rural stations designed to provide regional background and transport information. The NCore network is deployed in all 50 States, District of Columbia, and Puerto Rico with at least one station in each state and two or more stations in larger population states (California, Florida, Illinois, Michigan, New York, North Carolina, Ohio, Pennsylvania, and Texas). Both the STN and NCore networks which together comprise 76 locations with CSN measurements are intended to remain in operation indefinitely. The CSN measurements at STN and NCore stations operate on a 1-in-3-day sampling schedule. Another approximately 67 CSN stations, known as supplemental sites, are intended to be temporary locations used to support State Implementation Plan (SIP) development and other local or regional monitoring objectives. Supplemental CSN stations typically operate on a 1-in-6-day sampling schedule.

Specific chemical components of $PM_{2.5}$ are also measured through the IMPROVE monitoring program which supports regional haze characterization and tracks changes in visibility in Class I areas (e.g., large national parks) as well as many other rural and some urban areas. As of 2020, the IMPROVE network includes 110 base network monitoring locations and additional 46 locations operated as IMPROVE protocol sites where a state, local, or tribal monitoring agency has requested participation in the program. These IMPROVE protocol sites operate the same way as the IMPROVE program, but they may serve several monitoring objectives (e.g., SIP development) and are not explicitly tied to the Regional Haze Program. Samplers at IMPROVE stations operate on a 1-in-3-day sampling schedule. Together, the CSN and IMPROVE data provide chemical species information for $PM_{2.5}$ that are critical for use in health and epidemiologic studies to help inform reviews of the primary PM NAAQS and can be used to better understand visibility through calculation of light extinction using the IMPROVE algorithm to support reviews of the secondary PM NAAQS.

### A.4.4. U.S. EPA Criteria Gas Monitoring

Routine monitoring for criteria gases is performed at State and Local Air Monitoring Stations (SLAMS) using designated FRMs and FEMs. Table A.4-1 provides information on the FRMs and most widely deployed FEMs for the carbon monoxide (CO), ozone ($O_3$), nitrogen dioxide ($NO_2$), and $SO_2$ criteria gases. The current FRM for measuring concentrations of CO in ambient air is based on nondispersive infrared photometry (NDIR) and is detailed in 40 CFR Part 50 Appendix C (U.S. EPA, 2020a). To date only one FEM for CO has been designated and it is based upon mercury replacement-ultraviolet (UV) photometry. For $O_3$, the current FRM is based upon the chemiluminescent reaction between $O_3$ and ethylene or nitric oxide (NO) and is detailed in 40 CFR Part 50 Appendix D (U.S. EPA, 2011b). Currently FRM instruments based upon ethylene chemiluminescence are not available commercially, for this reason, an updated FRM that includes NO chemiluminescence was promulgated in 2015. The most widely used $O_3$ FEM is based upon UV photometry. This method, however, has been shown to have severe interferences in smoke and may result in significant overestimation of $O_3$ concentrations in smoke impacted areas (Long et al., In Press). The measurement principle for the $NO_2$ FRM detailed in 40 CFR Part 50 Appendix F (U.S. EPA, 2011a), consists of the catalytic conversion of $NO_2$ to NO followed by subsequent detection of the chemiluminescence reaction of NO with $O_3$. In addition to converting $NO_2$ to NO prior to detection, this method also converts high oxides of nitrogen (e.g., nitric acid [$HNO_3$], nitrous acid [$HNO_2$], particulate nitrate) to NO resulting in a potential overestimation of $NO_2$ concentrations. FEMs for $NO_2$ involve direct spectroscopic measurement of $NO_2$ and the replacement of the catalytic converter with a more specific photolytic converter prior to detection in the chemiluminescence method. Currently there are two FRMs for measuring concentrations of $SO_2$ in ambient air. The newer automated FRM is based on UV fluorescence and detailed in 40 CFR Part 50 Appendix A-1 (U.S. EPA, 2011c) and was promulgated in 2010. Prior to promulgation as an FRM, the UV fluorescence method was the most widely used FEM. The second $SO_2$ FRM is based upon the manual wet-chemical pararosaniline method and detailed in 40 CFR Part 50 Appendix A-2 (U.S. EPA, 2020b). Currently, this method is not employed in the routine monitoring of $SO_2$. For $O_3$, $NO_2$, and $SO_2$ automated open-path FEMs also exist based upon differential optical absorption spectroscopy (DOAS). These methods employ long measurement path lengths extending up to 1,000 m.

# A.5. SUPPLEMENTAL INFORMATION FOR CHAPTER 5

## A.5.1. Supplemental Tables for CHAPTER 5

**Table A.5 FUELS-1. Crosswalk between LANDFIRE existing vegetation types (LANDFIRE, 2014 Existing Vegetation Type) within the four scenario areas and an assigned Fuel Characteristic Classification System (FCCS) fuelbed. Fuelbed descriptions for each of the base fuelbeds can be found within the Fuel and Fire Tools (https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft).**

| EVT_ID | EVT Name | FCCS ID | Fuelbed Name |
|---|---|---|---|
| 11 | Ba Open Water | 0 | Barren |
| 31 | Bab Barren | 0 | Barren |
| 2001 | Sps Inter-Mountain Basins Sparsely Vegetated Systems | 0 | Barren |
| 2002 | Sps Mediterranean California Sparsely Vegetated Systems | 0 | Barren |
| 2003 | Sps North Pacific Sparsely Vegetated Systems | 0 | Barren |
| 2006 | Sps Rocky Mountain Alpine/Montane Sparsely Vegetated Systems | 0 | Barren |
| 2011 | Tr Rocky Mountain Aspen Forest and Woodland | 42 | Quaking aspen/Engelmann spruce forest |
| 2027 | Tr Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland | 37 | Ponderosa pine-Jeffrey pine forest |
| 2028 | Tr Mediterranean California Mesic Mixed Conifer Forest and Woodland | 214 | Giant sequoia-white fir-sugar pine forest |
| 2030 | Tr Mediterranean California Lower Montane Conifer Forest and Woodland | 16 | Jeffrey pine-ponderosa pine-Douglas fir-CA black oak forest |

**Table A.5 FUELS-1 (Continued): Crosswalk between LANDFIRE existing vegetation types (LANDFIRE, 2014 Existing Vegetation Type) within the four scenario areas and an assigned Fuel Characteristic Classification System (FCCS) fuelbed. Fuelbed descriptions for each of the base fuelbeds can be found within the Fuel and Fire Tools (https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft).**

| EVT_ID | EVT Name | FCCS ID | Fuelbed Name |
|---|---|---|---|
| 2032 | Tr Mediterranean California Red Fir Forest | 17 | Red fir forest |
| 2033 | Tr Mediterranean California Subalpine Woodland | 12 | Red fir-mountain hemlock-lodgepole pine-western white pine forest |
| 2037 | Tr North Pacific Maritime Dry-Mesic Douglas Fir-Western Hemlock Forest | 8 | Western hemlock-Douglas fir-western redcedar/vine maple forest |
| 2041 | Tr North Pacific Mountain Hemlock Forest | 238 | Pacific silver fir-mountain hemlock forest |
| 2042 | Tr North Pacific Mesic Western Hemlock-Silver Fir Forest | 238 | Pacific silver fir-mountain hemlock forest |
| 2043 | Tr Mediterranean California Mixed Evergreen Forest | 37 | Ponderosa pine-Jeffrey pine forest |
| 2044 | Tr Northern California Mesic Subalpine Woodland | 12 | Red fir-mountain hemlock-lodgepole pine-western white pine forest |
| 2045 | Tr Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest | 52 | Douglas fir-Pacific ponderosa pine/oceanspray forest |
| 2053 | Tr Northern Rocky Mountain Ponderosa Pine Woodland and Savanna | 53 | Pacific ponderosa pine forest |
| 2056 | Tr Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland | 59 | Subalpine fir-Engelmann spruce-Douglas fir-lodgepole pine forest |
| 2058 | Tr Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland | 12 | Red fir-mountain hemlock-lodgepole pine-western white pine forest |
| 2068 | Sh North Pacific Dry and Mesic Alpine Dwarf-Shrubland or Fell-Field or Meadow | 319 | Pacific silver fir-Sitka alder forest |
| 2080 | Sh Inter-Mountain Basins Big Sagebrush Shrubland | 233 | Sagebrush shrubland |
| 2083 | Sh North Pacific Avalanche Chute Shrubland | 319 | Pacific silver fir-Sitka alder forest |
| 2084 | Sh North Pacific Montane Shrubland | 237 | Huckleberry heather shrubland |
| 2098 | Sh California Montane Woodland and Chaparral | 44 | Scrub oak chaparral shrubland |
| 2106 | Sh Northern Rocky Mountain Montane-Foothill Deciduous Shrubland | 331 | Sitka alder-salmonberry shrubland |

**Table A.5 FUELS-1 (Continued): Crosswalk between LANDFIRE existing vegetation types (LANDFIRE, 2014 Existing Vegetation Type) within the four scenario areas and an assigned Fuel Characteristic Classification System (FCCS) fuelbed. Fuelbed descriptions for each of the base fuelbeds can be found within the Fuel and Fire Tools ([https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft](https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft)).**

| EVT_ID | EVT Name | FCCS ID | Fuelbed Name |
|---|---|---|---|
| 2125 | Sh Inter-Mountain Basins Big Sagebrush Steppe | 233 | Sagebrush shrubland |
| 2138 | He North Pacific Montane Grassland | 315 | Showy sedge-black alpine sedge grassland |
| 2139 | He Northern Rocky Mountain Lower Montane-Foothill-Valley Grassland | 506 | Idaho fescue-California oatgrass grassland |
| 2145 | He Rocky Mountain Subalpine-Montane Mesic Meadow | 530 | Temperate Pacific subalpine-montane wet meadow |
| 2152 | Tr California Montane Riparian Systems | 319 | Pacific silver fir-Sitka alder forest |
| 2154 | Tr Inter-Mountain Basins Montane Riparian Systems | 319 | Pacific silver fir-Sitka alder forest |
| 2167 | Tr Rocky Mountain Poor-Site Lodgepole Pine Forest | 22 | Mature lodgepole pine forest |
| 2171 | He North Pacific Alpine and Subalpine Dry Grassland | 315 | Showy sedge-black alpine sedge grassland |
| 2172 | Tr Sierran-Intermontane Desert Western White Pine-White Fir Woodland | 273 | Engelmann spruce-Douglas fir-white fir-ponderosa pine forest |
| 2173 | Tr North Pacific Wooded Volcanic Flowage | 28 | Ponderosa pine savanna |
| 2174 | Tr North Pacific Dry-Mesic Silver Fir-Western Hemlock-Douglas Fir Forest | 8 | Western hemlock-Douglas fir-western redcedar/vine maple forest |
| 2181 | He Introduced Upland Vegetation-Annual Grassland | 57 | Wheatgrass-cheatgrass grassland |
| 2182 | He Introduced Upland Vegetation-Perennial Grassland and Forbland | 57 | Wheatgrass-cheatgrass grassland |
| 2902 | Bau Developed-Low Intensity | 0 | Barren |
| 2905 | Bau Developed-Roads | 0 | Barren |
| 2914 | Dtc Urban Evergreen Forest | 22 | Mature lodgepole pine forest |
| 2916 | Dgr Urban Herbaceous | 66 | Bluebunch wheatgrass-bluegrass grassland |

**Table A.5 FUELS-1 (Continued): Crosswalk between LANDFIRE existing vegetation types (LANDFIRE, 2014 Existing Vegetation Type) within the four scenario areas and an assigned Fuel Characteristic Classification System (FCCS) fuelbed. Fuelbed descriptions for each of the base fuelbeds can be found within the Fuel and Fire Tools (https://www.fs.usda.gov/pnw/tools/fuel-and-fire-tools-fft).**

| EVT_ID | EVT Name | FCCS ID | Fuelbed Name |
|---|---|---|---|
| 2917 | Dsh Urban Shrubland | 401 | Holly-privet shrubland |
| 2926 | Dsh Developed Ruderal Shrubland | 401 | Holly-privet shrubland |

EVT = existing vegetation type; FCCS = Fuel Characteristic Classification System.

## Table A.5 FUELS-2 Disturbance update rules for past prescribed burns and wildfires.

| FCCS ID | Fuelbed Name | Recent Low-Severity Prescribed Burn | Past Wildfire 0−5 yr | Past Wildfire 5−10 yr |
|---|---|---|---|---|
| 8 | Western hemlock-Douglas fir-western redcedar/vine maple forest | 8_111 | 8_132 | 8_133 |
| 12 | Red fir-mountain hemlock-lodgepole pine-western white pine forest | 12_111 | 12_132 | 12_133 |
| 16 | Jeffrey pine-ponderosa pine-Douglas fir—CA black oak forest | 16_111 | 16_132 | 16_133 |
| 17 | Red fir forest | 17_111 | 17_132 | 17_133 |
| 22 | Mature lodgepole pine forest | 22_111 | 22_132 | 22_133 |
| 28 | Ponderosa pine savanna | 28_111 | 28_132 | 28_133 |
| 37 | Ponderosa pine-Jeffrey pine forest | 37_111 | 37_132 | 37_133 |
| 42 | Quaking aspen/Engelmann spruce forest | 42_111 | 42_132 | 42_133 |
| 44 | Scrub oak chaparral shrubland | 44_111 | 44_132 | 44_133 |
| 52 | Douglas fir-Pacific ponderosa pine/oceanspray forest | 52_111 | 52_132 | 52_133 |
| 53 | Pacific ponderosa pine forest | 53_111 | 53_132 | 53_133 |
| 57 | Wheatgrass-cheatgrass grassland | 57_111 | 57_132 | 57_133 |
| 59 | Subalpine fir-Engelmann spruce-Douglas fir-lodgepole pine forest | 59_111 | 59_132 | 59_133 |
| 66 | Bluebunch wheatgrass-bluegrass grassland | 66_111 | 66_132 | 66_133 |
| 214 | Giant sequoia-white fir-sugar pine forest | 214_111 | 214_132 | 214_133 |
| 233 | Sagebrush shrubland | 233_111 | 233_132 | 233_133 |
| 237 | Huckleberry heather shrubland | 237_111 | 237_132 | 237_133 |
| 238 | Pacific silver fir-mountain hemlock forest | 238_111 | 238_132 | 238_133 |
| 273 | Engelmann spruce-Douglas fir-white fir-ponderosa pine forest | 273_111 | 273_132 | 273_133 |
| 315 | Showy sedge-black alpine sedge grassland | 315_111 | 315_132 | 315_133 |

## Table A.5 FUELS-2 (Continued): Disturbance update rules for past prescribed burns and wildfires.

| FCCS ID | Fuelbed Name | Recent Low-Severity Prescribed Burn | Past Wildfire 0−5 yr | Past Wildfire 5−10 yr |
|---|---|---|---|---|
| 319 | Pacific silver fir-Sitka alder forest | 319_111 | 319_132 | 319_133 |
| 331 | Sitka alder-salmonberry shrubland | 331_111 | 331_132 | 331_133 |
| 401 | Holly-privet shrubland | 401_111 | 401_132 | 401_133 |
| 506 | Idaho fescue-California oatgrass grassland | 506_111 | 506_132 | 506_133 |
| 530 | Temperate Pacific subalpine-montane wet meadow | 530_111 | 530_132 | 530_133 |

FCCS = Fuel Characteristic Classification System.

## Table A.5 SPECIATION-1 Speciation profiles used for converting volatile organic compound (VOC) and $PM_{2.5}$ to model species.

| Prescribed Fires | | | |
|---|---|---|---|
| Profile ID | Pollutant | CB6 group | Mass Fraction |
| 95423 | TOG | ALD2_PRIMARY | 0.0223 |
| 95423 | TOG | FORM_PRIMARY | 0.0445 |
| 95423 | TOG | SOAALK | 0.009503 |
| 95423 | TOG | ACET | 0.0115 |
| 95423 | TOG | ALD2 | 0.0223 |
| 95423 | TOG | ALDX | 0.036 |
| 95423 | TOG | BENZ | 0.005976 |
| 95423 | TOG | CH4 | 0.0968 |
| 95423 | TOG | ETH | 0.0275 |
| 95423 | TOG | ETHA | 0.0132 |
| 95423 | TOG | ETHY | 0.006216 |
| 95423 | TOG | ETOH | 0.004761 |
| 95423 | TOG | FORM | 0.0445 |
| 95423 | TOG | IOLE | 0.0107 |
| 95423 | TOG | ISOP | 0.001913 |
| 95423 | TOG | KET | 0.005659 |
| 95423 | TOG | MEOH | 0.0501 |
| 95423 | TOG | NAPH | 0.006475 |
| 95423 | TOG | NVOL | 0.004562 |
| 95423 | TOG | OLE | 0.0553 |
| 95423 | TOG | PAR | 0.3296 |
| 95423 | TOG | PRPA | 0.004821 |
| 95423 | TOG | TERP | 0.0129 |
| 95423 | TOG | TOL | 0.0476 |
| 95423 | TOG | UNR | 0.1636 |
| 95423 | TOG | XYLMN | 0.038 |
| Prescribed Fires: VOC->TOG factor = 1.14341685 | | | |

| Wild Fires | | | |
|---|---|---|---|
| Profile ID | Pollutant | CB6 group | Mass Fraction |
| 95424 | TOG | ACET | 0.0115 |
| 95424 | TOG | ALD2 | 0.0224 |
| 95424 | TOG | ALDX | 0.0353 |
| 95424 | TOG | BENZ | 0.006012 |
| 95424 | TOG | CH4 | 0.1095 |
| 95424 | TOG | ETH | 0.0273 |
| 95424 | TOG | ETHA | 0.0161 |
| 95424 | TOG | ETHY | 0.005622 |
| 95424 | TOG | ETOH | 0.004785 |
| 95424 | TOG | FORM | 0.0336 |
| 95424 | TOG | IOLE | 0.0108 |
| 95424 | TOG | ISOP | 0.001929 |
| 95424 | TOG | KET | 0.005694 |
| 95424 | TOG | MEOH | 0.0308 |
| 95424 | TOG | NAPH | 0.006505 |
| 95424 | TOG | NVOL | 0.004606 |
| 95424 | TOG | OLE | 0.0507 |
| 95424 | TOG | PAR | 0.343 |
| 95424 | TOG | PRPA | 0.007611 |
| 95424 | TOG | TERP | 0.013 |
| 95424 | TOG | TOL | 0.0492 |
| 95424 | TOG | UNR | 0.1647 |
| 95424 | TOG | XYLMN | 0.0393 |
| Wildfires: VOC->TOG factor = 1.16417442 | | | |

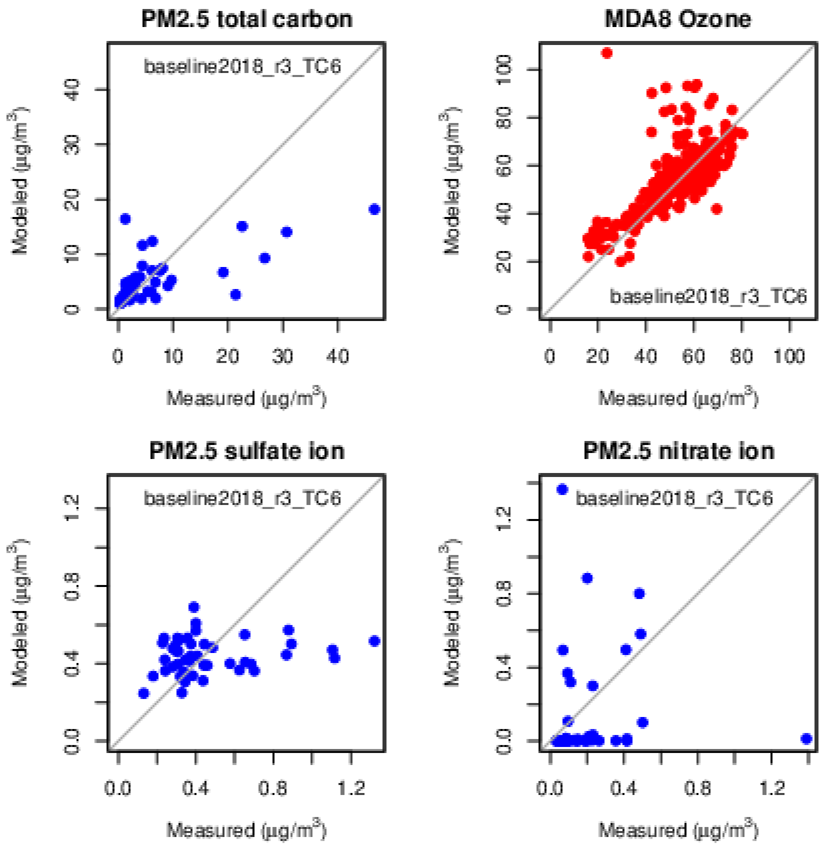
| Wild and Prescribed Fires | | | |
|---|---|---|---|
| Profile ID | Pollutant | CMAQ specie | Mass Fraction |
| 3766AE6 | PM2_5 | PNO3 | 2.810E-04 |
| 3766AE6 | PM2_5 | POC | 4.688E-01 |
| 3766AE6 | PM2_5 | PSI | 6.200E-04 |
| 3766AE6 | PM2_5 | PNA | 1.220E-04 |
| 3766AE6 | PM2_5 | PSO4 | 1.332E-03 |
| 3766AE6 | PM2_5 | PTI | 1.500E-05 |
| 3766AE6 | PM2_5 | PNH4 | 1.105E-03 |
| 3766AE6 | PM2_5 | PEC | 3.227E-02 |
| 3766AE6 | PM2_5 | PK | 1.203E-03 |
| 3766AE6 | PM2_5 | PNCOM | 3.281E-01 |
| 3766AE6 | PM2_5 | PAL | 1.540E-04 |
| 3766AE6 | PM2_5 | PCA | 3.693E-03 |
| 3766AE6 | PM2_5 | PCL | 2.070E-03 |
| 3766AE6 | PM2_5 | PFE | 1.800E-04 |
| 3766AE6 | PM2_5 | PMG | 1.790E-04 |
| 3766AE6 | PM2_5 | PMN | 5.000E-06 |
| 3766AE6 | PM2_5 | PMOTHR | 1.599E-01 |

CMAQ = Community Multiscale Air Quality; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; VOC = volatile organic compound.

**Table A.5-1 Model performance metrics estimated for ozone and major speciated components of $PM_{2.5}$. Performance metrics include mean bias, mean error, normalized mean bias, normalized mean error, and correlations coefficient.**

| Modeling Period | Specie | Data subset | N | Mean Bias | Mean Error | Normalized Mean Bias (%) | Normalized Mean Error (%) | $r^2$ |
|---|---|---|---|---|---|---|---|---|
| July 2018 | MDA8 ozone | None (all data) | 273 | 2.24 | 7.39 | 4.32 | 14.26 | 0.52 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | 79 | 7.97 | 11.64 | 12.75 | 18.62 | 0.07 |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | 89 | -3.62 | 7.27 | -5.42 | 10.90 | 0.16 |
| | PM2.5 nitrate ion | None (all data) | 46 | -0.07 | 0.22 | -34.82 | 110.21 | 0.01 |
| | PM2.5 sulfate ion | None (all data) | 46 | -0.03 | 0.19 | -5.96 | 41.28 | 0.04 |
| | PM2.5 total carbon | None (all data) | 46 | -1.20 | 4.29 | -18.34 | 65.85 | 0.43 |
| Sep 2019 | MDA8 ozone | None (all data) | 533 | 3.79 | 5.58 | 10.89 | 16.03 | 0.57 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | | | | | | |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | | | | | | |
| | PM2.5 nitrate ion | None (all data) | 82 | -0.03 | 0.10 | -25.63 | 84.24 | 0.30 |
| | PM2.5 sulfate ion | None (all data) | 82 | 0.23 | 0.26 | 73.66 | 84.20 | 0.15 |
| | PM2.5 total carbon | None (all data) | 80 | 0.87 | 1.11 | 89.62 | 114.36 | 0.12 |
| Feb/Mar 2019 | MDA8 ozone | None (all data) | 576 | 6.03 | 7.11 | 15.65 | 18.44 | 0.16 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | | | | | | |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | | | | | | |
| | PM2.5 nitrate ion | None (all data) | 163 | -0.14 | 0.15 | -80.44 | 85.33 | 0.14 |
| | PM2.5 sulfate ion | None (all data) | 167 | 0.30 | 0.31 | 164.85 | 166.27 | 0.63 |
| | PM2.5 total carbon | None (all data) | 169 | 0.15 | 0.36 | 32.18 | 78.73 | 0.30 |
| Aug/Sep 2015 | MDA8 ozone | None (all data) | 11,510 | 0.64 | 6.53 | 1.29 | 13.08 | 0.66 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | 2,266 | 1.26 | 8.41 | 1.88 | 12.54 | 0.22 |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | 2,660 | -6.47 | 8.76 | -9.24 | 12.50 | 0.31 |
| | PM2.5 nitrate ion | None (all data) | 720 | -0.39 | 0.47 | -70.56 | 83.73 | 0.20 |
| | PM2.5 sulfate ion | None (all data) | 722 | -0.01 | 0.33 | -0.92 | 44.37 | 0.25 |
| | PM2.5 total carbon | None (all data) | 536 | -0.57 | 1.82 | -18.92 | 59.91 | 0.37 |
| Aug/Sep 2010 | MDA8 ozone | None (all data) | 11,764 | 7.33 | 10.09 | 14.31 | 19.69 | 0.59 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | 5,373 | 9.89 | 12.25 | 15.78 | 19.53 | 0.22 |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | 3,582 | 2.76 | 8.80 | 3.91 | 12.47 | 0.27 |
| | PM2.5 nitrate ion | None (all data) | 540 | -0.16 | 0.24 | -65.37 | 96.29 | 0.02 |
| | PM2.5 sulfate ion | None (all data) | 541 | -0.01 | 0.24 | -2.31 | 42.02 | 0.16 |
| | PM2.5 total carbon | None (all data) | 549 | 1.34 | 1.83 | 88.98 | 121.65 | 0.05 |
| Oct 2014 | MDA8 ozone | None (all data) | 1,308 | -2.46 | 7.68 | -4.40 | 13.73 | 0.52 |
| | MDA8 ozone | Modeled MDA8 O3 > 60 ppb | 268 | -2.99 | 7.89 | -4.31 | 11.38 | 0.32 |
| | MDA8 ozone | Observed MDA8 O3 > 60 ppb | 503 | -10.15 | 10.87 | -14.54 | 15.57 | 0.30 |
| | PM2.5 nitrate ion | None (all data) | 77 | -0.21 | 0.32 | -50.54 | 75.59 | 0.43 |
| | PM2.5 sulfate ion | None (all data) | 77 | -0.12 | 0.21 | -23.80 | 42.91 | 0.26 |
| | PM2.5 total carbon | None (all data) | 71 | 0.77 | 1.03 | 66.70 | 89.49 | 0.75 |

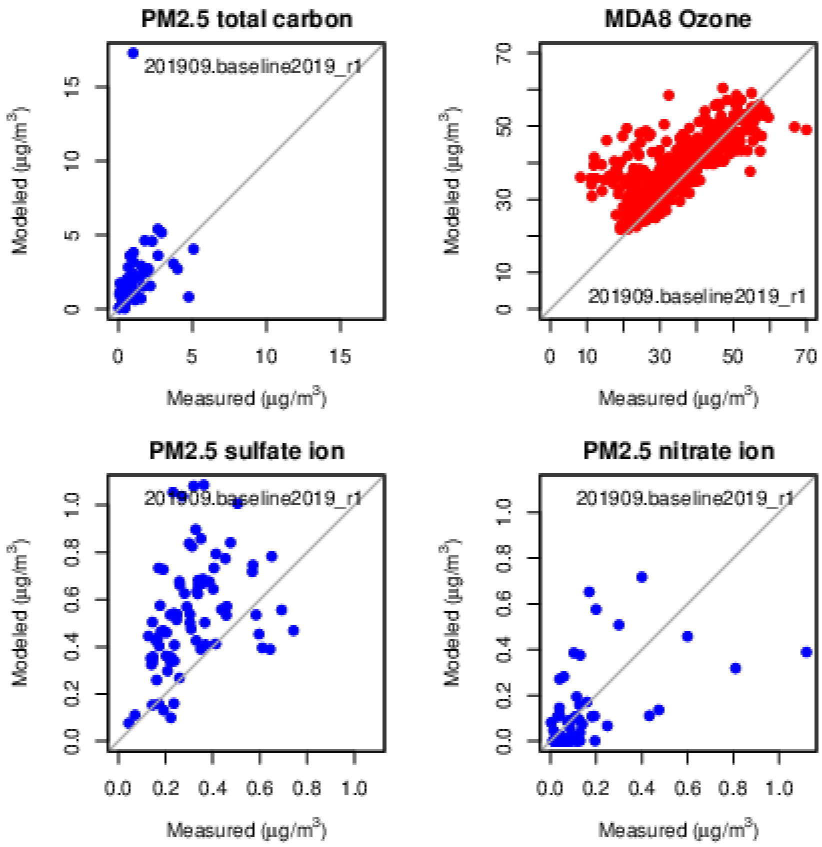
Metrics are aggregated over all monitors in the model domain for each modeling period.




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm; TC6 = Timber Crater 6.

Model prediction-observation pairs represent monitor locations in the study area region during the 2018 modeling period used to support the Timber Crater 6 scenarios.

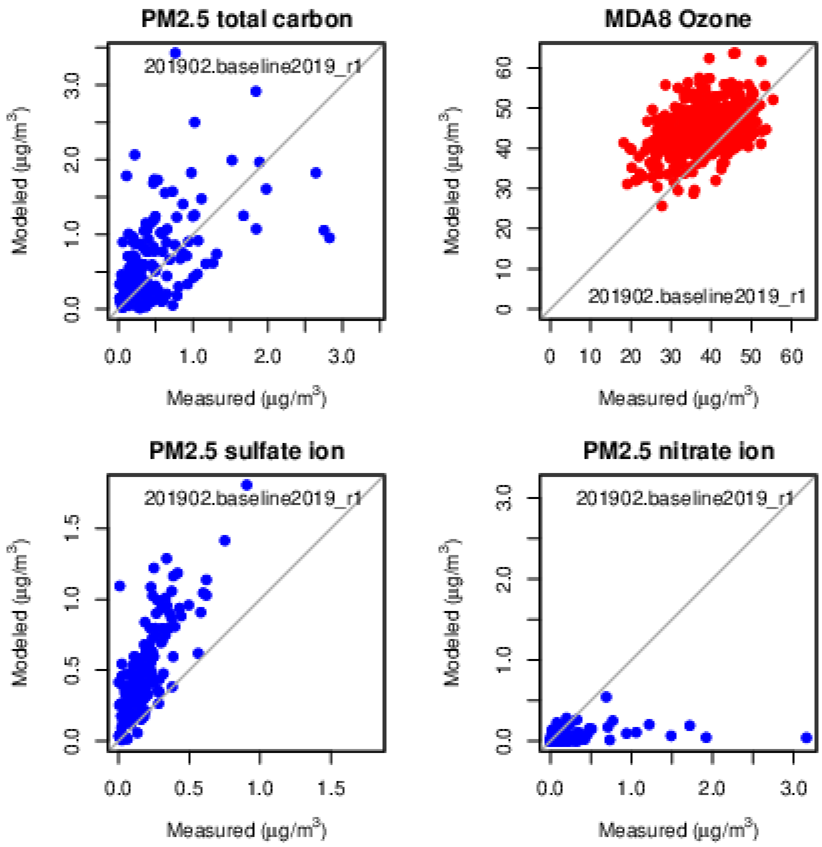
**Figure A.5 MPE-1 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**




MDA8 = maximum daily 8-hour average; µg/m³ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Model prediction-observation pairs represent monitor locations in the study area region during the 2019 fall modeling period used to support the Timber Crater 6 prescribed fire scenarios.

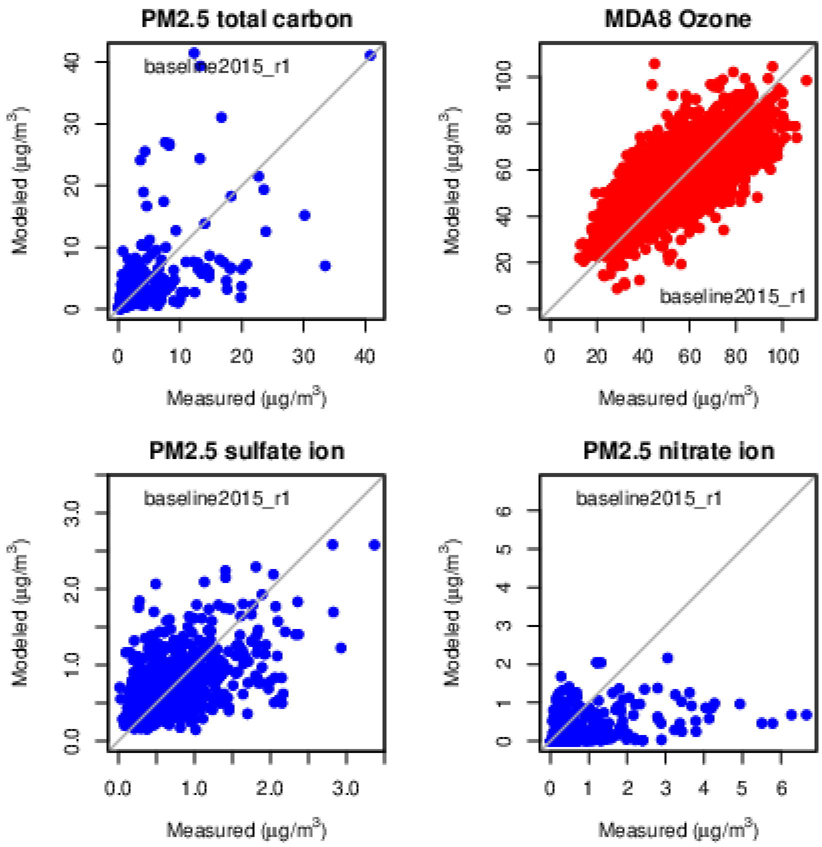
**Figure A.5 MPE-2 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Model prediction-observation pairs represent monitor locations in the study area region during the 2019 winter modeling period used to support the hypothetical slash/pile burn scenarios.

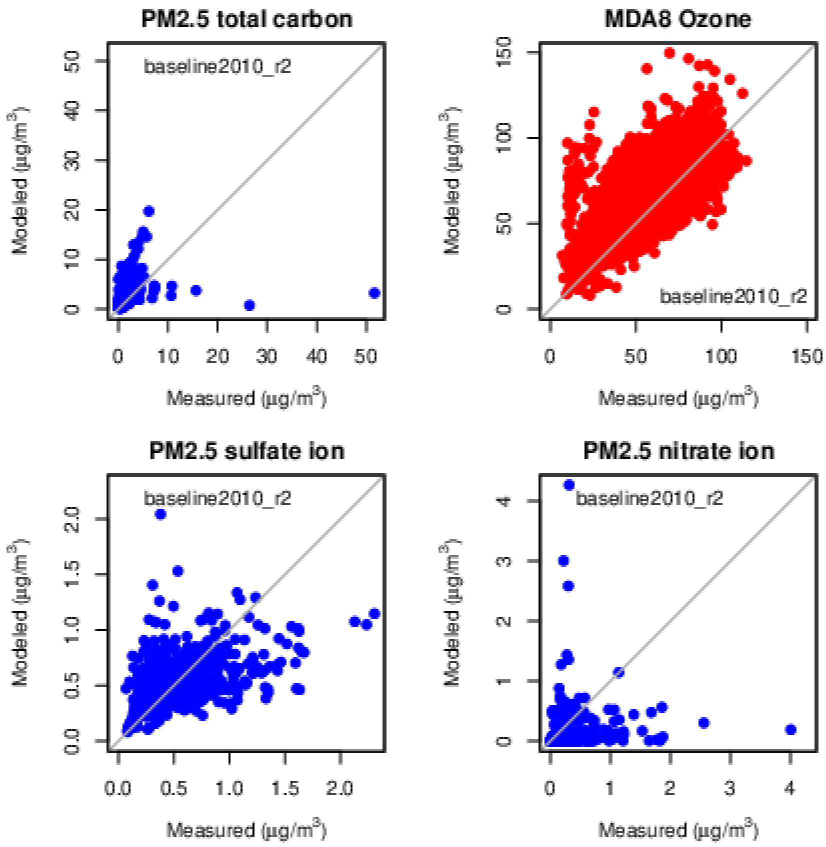
**Figure A.5 MPE-3 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Model prediction-observation pairs represent monitor locations in the study area region during the 2015 modeling period used to support the Rough Fire scenarios.

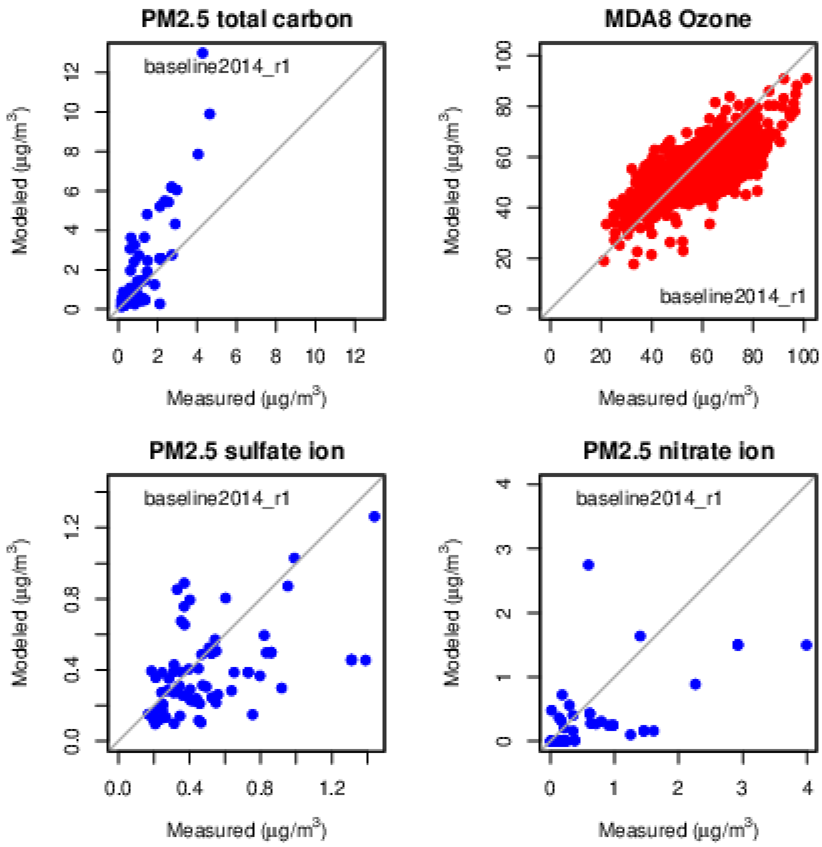
**Figure A.5 MPE-4 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Model prediction-observation pairs represent monitor locations in the study area region during the 2010 modeling period used to support the Sheep Complex Fire scenario.

**Figure A.5 MPE-5 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**




MDA8 = maximum daily 8-hour average; µg/m$^3$ = micrograms per cubic meter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

Model prediction-observation pairs represent monitor locations in the study area region during the 2014 modeling period used to support the hypothetical Boulder Creek Unit 1 prescribed fire scenario.

**Figure A.5 MPE-6 Daily average maximum daily 8-hour average (MDA8) ozone and speciated components of $PM_{2.5}$ including total carbon, sulfate ion, and nitrate ion model predictions paired with routine surface monitor data in space and time.**

## A.5.2. Supplemental Materials for Section 5.2.2: Surface Fuel Loads

### A.5.2.1. Introduction

Supplementary materials included here for Section 5.2.2 provide additional details on methods used to develop LEMMA-initialized Visualizing Ecosystem Land Management Assessments (VELMA) applications and associated VELMA-Fuel Characteristic Classification System (FCCS) fuelbed databases for the Timber Crater 6 (TC6), Rough, and Sheep Complex case study applications.

Extensive technical and quality assurance documentation is referenced in U.S. EPA's ScienceHub data repository (https://catalog.data.gov/dataset/epa-sciencehub).

#### A.5.2.2. Quality Assurance Project Plan

U.S. EPA has established quality assurance requirements that must be followed within U.S. EPA and by extramural contractors for all work performed that involves environmental data collection, use or reporting, including modeling-related activities. Consistent with these requirements, all work performed and reported herein using U.S. EPA's VELMA model follow the *VELMA Modeling Quality Assurance Project Plan (QAPP)* (McKane, 2020).

The VELMA Modeling QAPP describes quality assurance practices relevant to all VELMA applications, such as those described in this report. These practices concern issues of data quality, calibration, validation, propagation of error and other considerations outlined in the Table of Contents (Figure A.5-1).

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VELMA = Visualizing Ecosystem Land Management Assessments.

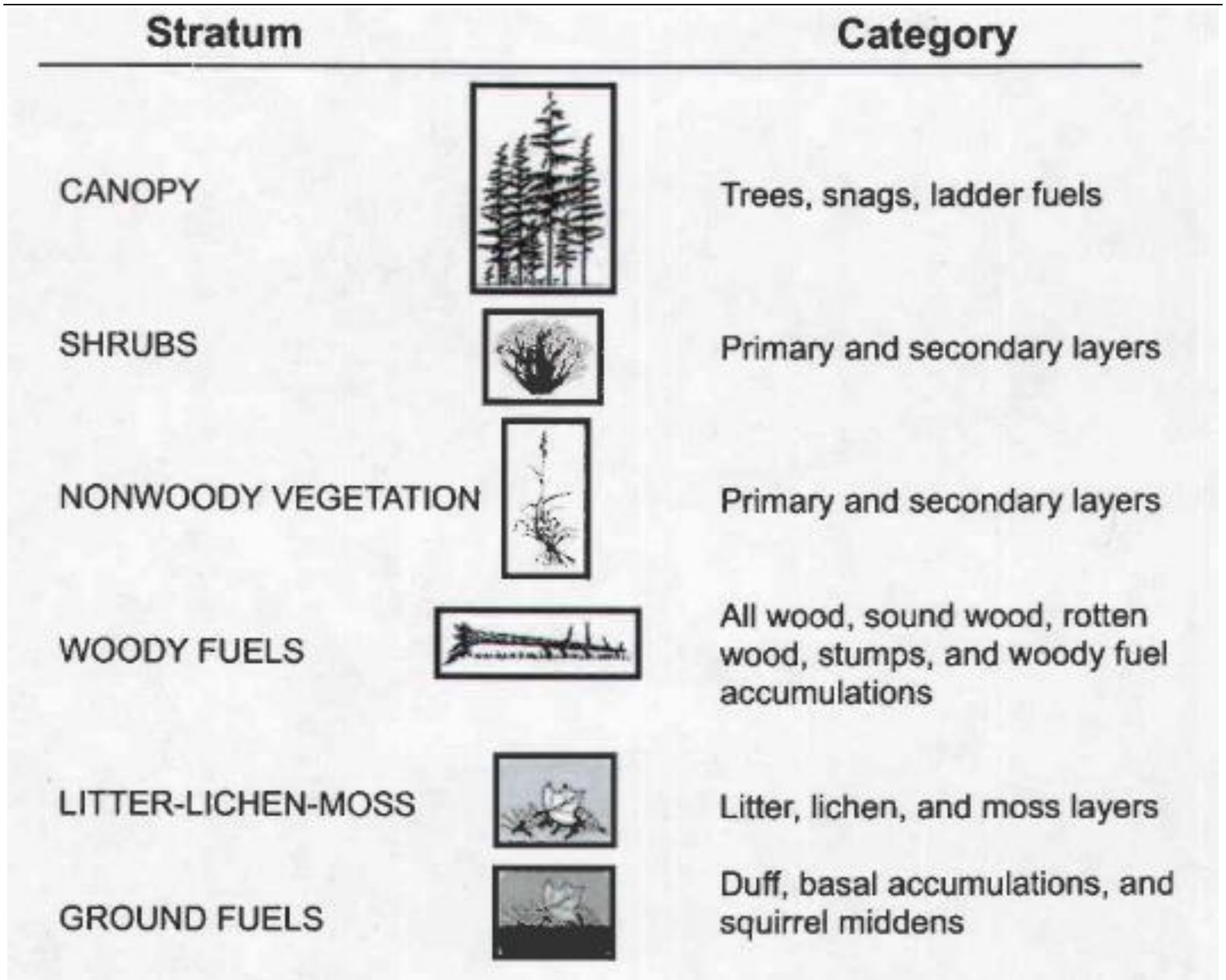
**Figure A.5-1 Quality assurance topics addressed in the Visualizing Ecosystem Land Management Assessments (VELMA) Modeling Quality Assurance Project Plan (McKane, 2020).**

The QAPP also provides the U.S. EPA computer server secure location containing the VELMA applications developed for this project. This information includes VELMA model input and output files used for model calibration and validation, references and other documentation supporting these activities.

### A.5.2.3. Methods

#### A.5.2.3.1. Characterizing Surface Fuel Load Estimates Using the Fuel Characteristics Classification System

The FCCS is a consistent, scientifically based framework that provides a catalogue of fuelbeds across the U.S. that coincide with various cover types, including grasslands, shrublands, woodlands, and forests (Ottmar et al., 2007). In FCCS, a fuelbed is defined as a relatively homogeneous landscape unit that represents a unique combustion environment. Each fuelbed is separated into categories and subcategories that depict the loading available for fuel and vary depending on the landscape unit being represented (Figure A.5-2).




FCCS = Fuel Characteristic Classification System.

**Figure A.5-2 Fuelbed strata and categories included in the Fuel Characteristic Classification System [FCCS; Ottmar et al. (2007)].**

The fuel load values (U.S. tons C/acre) for each fuelbed category are derived from scientific literature, fuel databases, and expert knowledge. Further information can be found in Ottmar et al. (2007). For the purposes of this investigation, the FCCS fuelbeds were matched to case study regional boundaries using existing vegetation type layers obtained from LANDFIRE (http://landfire.cr.usgs.gov/viewer/). The resulting FCCS data then comprised a raster file that described unique identification codes that represented various fuelbed types as well as a look-up table that provided fuelbed loading values (in tons/acre) for each of the fuelbed categories and subcategories.

While FCCS captures the general diversity of available fuels found throughout the U.S., the fuel loadings are summarized across all plots within a particular vegetation classification category. Studies suggest that accuracy of FCCS and similar vegetation-based approaches are limited due to the high spatial and temporal variability of fuels, site-specific conditions, and the presence of disturbances including harvests, prescribed fires, and other disturbances (Lutes et al., 2009; Brown and See, 1986, 1981).

### A.5.2.4. Improving Fuel Characteristic Classification System (FCCS) Surface Fuel Load Estimates Using Visualizing Ecosystem Land Management Assessments (VELMA), a Spatially Explicit, Process-Based Ecohydrological Model

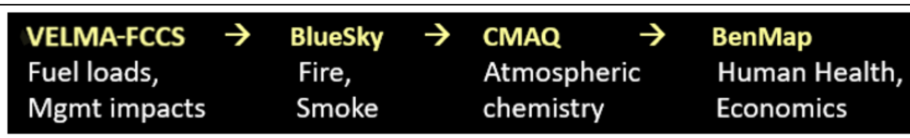
Due to the limitations listed above, a model-based approach was explored to supplement existing FCCS data to more accurately characterize surface fuel loads that could then be used to simulate air quality impacts and the effects of prescribed fire for the various real and hypothetical case studies described in CHAPTER 5 of this report.

#### A.5.2.4.1. Overview of Visualizing Environmental Land Management Assessments (VELMA)

The VELMA model is a spatially distributed (grid-based) ecohydrological model that simulates integrated daily responses of vegetation, soil, and hydrologic components to changes in climate, land use and land cover. VELMA does this through its linkage of a land surface hydrology model with a terrestrial biogeochemistry model. The hydrology model simulates water infiltration and redistribution, evapotranspiration (ET) and surface and subsurface runoff. The biogeochemistry model simulates plant growth and mortality, formation and turnover of detritus and soil organic matter, and associated cycling of carbon and nutrients. The interaction of hydrological and biogeochemical processes in the model constrain changes in ecosystem structure and function in response to various environmental changes including management. VELMA simulates land management activities in a spatially and temporally explicit manner, such as harvest, prescribed fire, and wildfire, among other potential treatments (McKane et al., 2014). VELMA has been applied in many terrestrial ecosystem types, including forests, grasslands, agricultural lands, floodplains, alpine and urban landscapes (Barnhart et al., 2021; Hoghooghi et al., 2018; McKane et al., 2016; Barnhart et al., 2015; Abdelnour et al., 2013; Abdelnour et al., 2011). Particularly in forests and rangelands, it has been used to simulate effects of fire and harvest on ecosystem structure and function and subsequent recovery, including impacts on ecosystem services vital to human health and well-being (McKane et al., 2018; Yee et al., 2017).

As noted above, a main advantage of using VELMA to supplement FCCS surface fuel load estimates are that FCCS data varies by fuelbed but each fuelbed does not vary spatially or temporally. This means that two cells with the same fuelbed classification will give the exact same surface fuel load estimations, regardless of their location in the watershed. Conversely, VELMA can be initialized using spatially distributed aboveground biomass or forest age data that are location and condition-specific to a defining year. During a simulation, live and dead biomass pools within any watershed pixel can change daily based as a function of water availability, temperature, soil type, and landscape position, as well as any management actions (e.g., clearcutting, thinning, fire) that the user has specified. Therefore, VELMA can capture spatial variations in live and dead biomass pools attributable to spatially and temporally varying conditions within the landscape. For example, VELMA's forest harvest and forest burn tools make it possible to simulate reductions in live and dead fuel loads and subsequent rates of recovery.

As discussed in Section 5.2.2, our goal in combining FCCS and VELMA fuelbed information is to improve the accuracy of spatial and temporal surface fuel load estimates and, therefore, the accuracy of the BlueSky and Community Multiscale Air Quality (CMAQ) air quality models and, ultimately, the accuracy of Benefits Mapping and Analysis Program (BenMAP) and associated tools used to assess air quality impacts on human health at local and regional scales (Figure A.5-3).




BenMAP = Benefits Mapping and Analysis Program; CMAQ = Community Multiscale Air Quality; FCCS = Fuel Characteristic Classification System; VELMA = Visualizing Ecosystem Land Management Assessments.

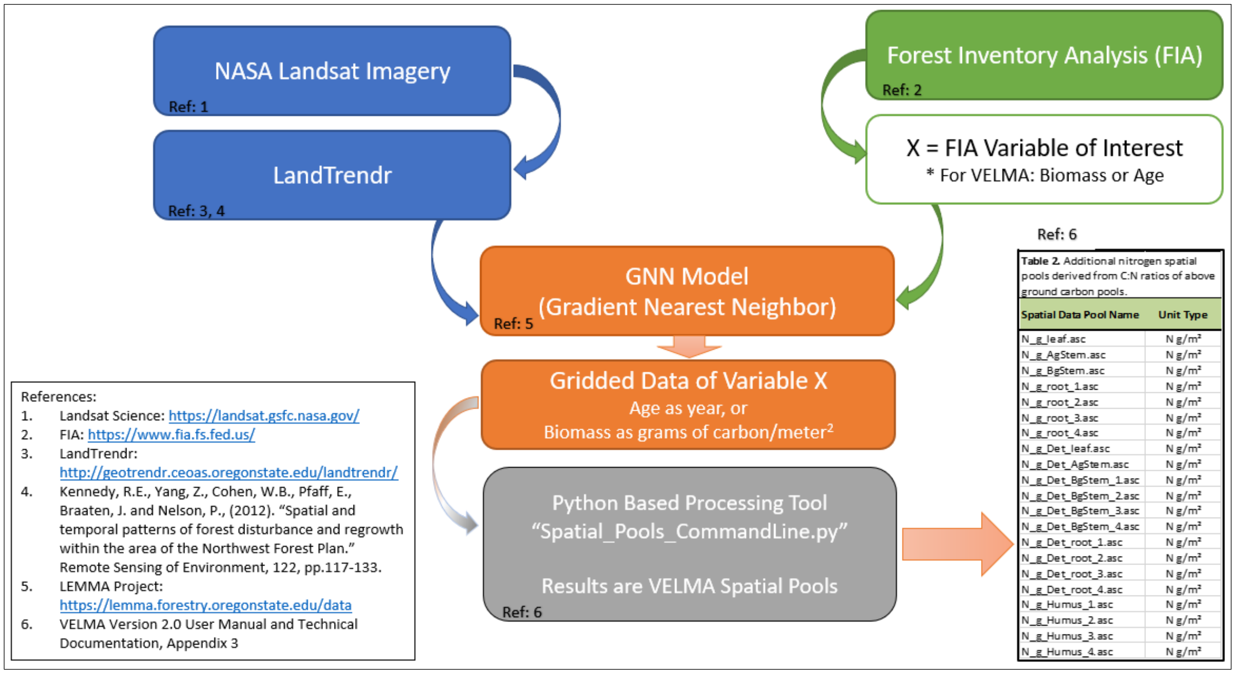
**Figure A.5-3 Generalized model-to-model workflow for this study.**

##### A.5.2.4.1.1. Visualizing Ecosystem Land Management Assessments (VELMA) Inputs and Initialization

Model inputs and simulation methods varied depending on the case study being implemented—Timber Crater 6, Rough, or Sheep Complex. In this section we summarize the full range of methods and discuss in subsequent sections how specific steps were implemented for each case study. These steps include:

1. Acquire satellite-based LEMMA data to develop a spatial (30-m) description of total aboveground forest biomass and stand age for a specified landscape and year (Figure A.5-4).
2. Use Step 1 LEMMA data to generate spatial carbon and nitrogen pools for VELMA's 13 plant and soil state variables, per U.S. EPA VELMA documentation, *How To Create VELMA Spatial Chemistry Pools.docx* (McKane et al., 2014). This procedure resulted in carbon and nitrogen pool look-up tables for stand ages ranging from 0 to 400 years-old. See Figure A.5-5 for an example illustrating age-related (successional) changes in aboveground stem biomass.
3. Initialize VELMA using Step 2 spatial plant and soil carbon and nitrogen pool data. Initialization also requires the additional environmental spatial data described in Table A.5-2.

4. Use the fully initialized VELMA model (Step 3) to conduct specified actual and hypothetical fire treatments for case study locations. Note: depending on a case study's end goals of combining FCCS and VELMA fuelbed information, Steps 3 and 4 may not be necessary.




LEMMA = Landscape Ecology, Modeling, Mapping, and Analysis; NASA = National Aeronautics and Space Administration; FIA = Forest Inventory Analysis; GNN = gradient nearest neighbor; VELMA = Visualizing Ecosystem Land Management Assessments.

**Figure A.5-4 Procedures for acquiring Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA; LandTrendr/gradient nearest neighbor [GNN]) high-resolution (30-m) satellite data used to initialize Visualizing Ecosystem Land Management Assessments (VELMA) for the case studies described in this report.**

**Table A.5-2 Spatial data type, source, and years used to initialize Visualizing Ecosystem Land Management Assessments (VELMA) for case study simulations.**

| VELMA Data Type | Source | Year |
|---|---|---|
| *Timber Crater 6 Setup* | | |
| Weather drivers | PRISM: precipitation and mean air temperature<br>https://prism.oregonstate.edu/explorer/ | 2010 through 2019 |
| Elevation | USDA Data Gateway DEM):<br>https://datagateway.nrcs.usda.gov/GDGOrder.aspx | 2019 |
| Age | LEMMA:<br>https://lemma.forestry.oregonstate.edu/data | 2010 |
| Biomass | LEMMA:<br>https://lemma.forestry.oregonstate.edu/data<br>*Note: LEMMA above ground biomass undergoes a unit conversion, then processed through VELMA's preprocessing tool "Spatial_Pools_Py3_CommandLine.py" script. | 2010 |
| Coverage | Uniform<br>*Note: FCCS coverage for nonforested cells was included during the combining of FCCS and VELMA fuelbed information step. | NA |
| Soils | Uniform (TC6 per Remillard (1999)) | NA |
| *Rough and Sheep Complex Setups* | | |
| Age | LEMMA:<br>https://lemma.forestry.oregonstate.edu/data | 2012 |
| Biomass | LEMMA:<br>https://lemma.forestry.oregonstate.edu/data<br>*Note: LEMMA above ground biomass undergoes a unit conversion, then processed through VELMA's preprocessing tool "Spatial_Pools_Py3_CommandLine.py" script. | 2012 |
| Coverage | Uniform<br>*Note: FCCS coverage for nonforested cells was included during the combining of FCCS and VELMA fuelbed information step. | NA |

DEM = digital elevation model; FCCS = Fuel Characteristic Classification System; LEMMA = Landscape Ecology, Modeling, Mapping, and Analysis; TC6 = Timber Crater 6; USDA = U.S. Department of Agriculture; VELMA = Visualizing Ecosystem Land Management Assessments.

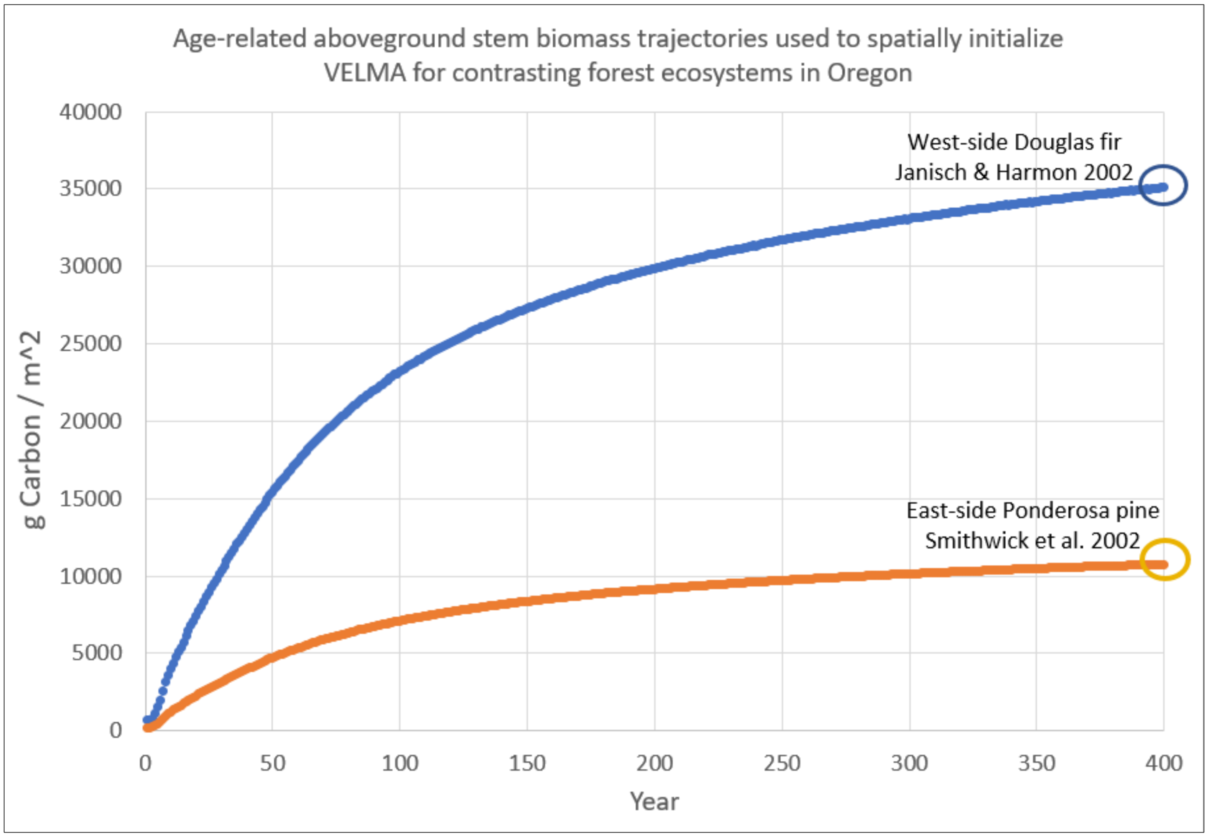
Timber Crater 6 case study. This study site was set up using Steps 1 through 4 so that potential alternate scenarios could be completed prior to the actual forest fire event date. Model initialization occurs for the Year 2010 to leave open the possibility of simulating prefire land management actions prior to the actual August 2018 actual fire. Simulations carried out to date were restricted to actual landscape conditions.

Rough and Sheep Complex case studies. These case study sites were developed only up to Step 1, above, then jumped directly to the step of combining FCCS and VELMA fuelbed information, described in Section A.5.2.4.1.5. In this case, due to fortuitous data timing, the VELMA biomass data was acquired from the time-zero LEMMA biomass and age data initialization and represented the forest state for the actual scenario. If future work requires alternate scenarios of land management actions within these sites, LEMMA biomass and age data initialization should occur for years preceding the actual fires to allow VELMA to be initialized and set up to simulate prefire fuelbed treatments.

LEMMA data capture the effects of fine-scale annual changes in aboveground forest biomass associated with fire, harvest, road construction and other disturbances that have occurred since 1990 across California, Oregon, and Washington. LEMMA data quality is keyed to U.S. Forest Service (USFS) Forest Inventory and Analysis (FIA) survey data, along with extensive local- and regional-scale validation against independent LiDAR-based forest survey methods (Bell et al., 2018).

In practice, age-related biomass trajectories Figure A.5-5) take the form of look-up tables, developed using the LEMMA-based procedure described for steps 1 and 2 in this section for initializing spatial (30-m grid) carbon and nitrogen pools for VELMA's 13 plant and soil state variables across a landscape. See Figure A.5-9 for a 3-D visualization of spatial variability in aboveground live forest biomass for a LEMMA-initialized landscape for the TC6 case study. Figure A.5-10 is a histogram showing the number of 30-m pixels represented in Figure A.5-9 across the full range of aboveground biomass values for this case study domain (Figure A.5-8).

Note that age-related biomass trajectories, such as the example in Figure A.5-5, are used for the sole purpose of spatially initializing time zero plant and soil carbon and nitrogen pools for landscapes simulated using VELMA. Simulated trajectories from Day 1 forward are a function of environmental forcing variables, such as climate, nutrient availability, and disturbances. For example, simulation of a heavily irrigated and fertilized Ponderosa pine forest could potentially follow a steeper trajectory than that shown for ponderosa pine (orange line) in Figure A.5-5.

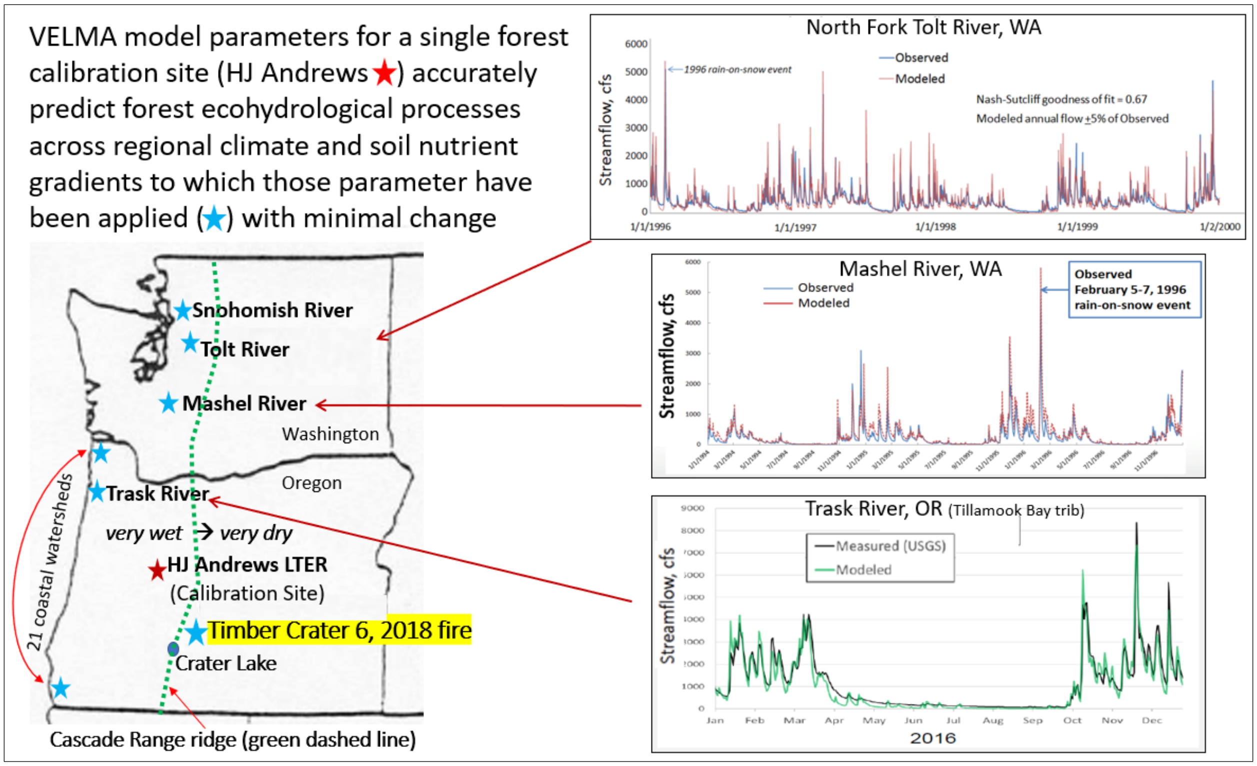



VELMA = Visualizing Ecosystem Land Management Assessments; g carbon/$m^2$ = grams of carbon per square meter.

**Figure A.5-5 Age-related changes (successional trajectories) in aboveground stem biomass for Douglas fir and ponderosa pine growing in western and eastern Oregon, respectively.**

#### A.5.2.4.1.2. Model Calibration and Performance

Prior to this study, Pacific Northwest VELMA applications focused on productive, high biomass Douglas fir/western hemlock forest ecosystems growing on the moist west side of the Cascade Range in Oregon and Washington (annual precipitation range ~2,000−3,500 mm). For those applications a single set of VELMA model parameters, calibrated for the HJ Andrews Experimental Forest (McKane et al., 2014; Abdelnour et al., 2013; Abdelnour et al., 2011), has accurately simulated hydrological and biogeochemical responses across dozens of watersheds in western Oregon and Washington, after accounting for location-specific climate and soil nutrient status (Figure A.5-6).




cfs = cubic feet per second; TC6 = Timber Crater 6; VELMA = Visualizing Ecosystem Land Management Assessments.
The location of the TC6 study site on the drier east side of the Cascade Range is shown for reference. Figure updated from McKane et al. (2018).

**Figure A.5-6 Locations of various coniferous forest sites in western Oregon and Washington for which Visualizing Ecosystem Land Management Assessments (VELMA) has been successfully applied regionally on the basis of a single, broadly applicable set of model parameters developed for the HJ Andrews Experimental Forest.**

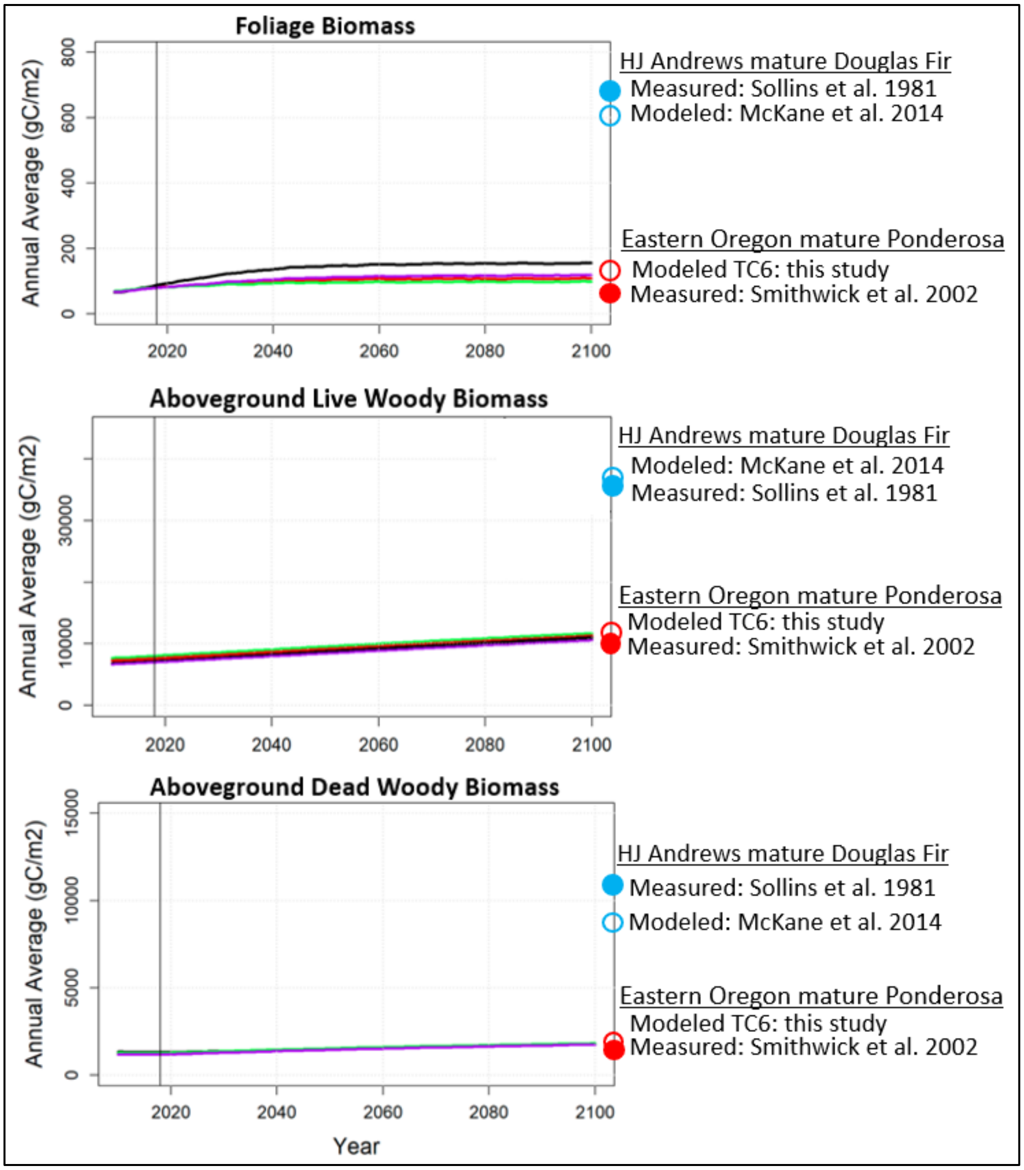
To explore whether the same west-side HJ Andrews VELMA calibration parameters could be successfully applied to the much drier and nutrient-poor east-side TC6 study site (Figure A.5-6), we used the procedures outlined in Section A.5.2.4.1.1

to initialize the HJA Andrews calibration for TC6, replacing LEMMA-based HJ Andrews Douglas fir forest biomass values that are several times higher than east-side coniferous forest values, including those at TC6 (Figure A.5-5).

No other changes were made except to (1) drive the TC6-initialized HJ Andrews calibration with local TC6 daily climate drivers (Table A.5-2); and (2) replace HJ Andrews soil carbon and nitrogen values with those for TC6 (Remillard, 1999). Regarding (1), average annual precipitation is about 500 mm at TC6, about 25% as much as the HJA Andrews site receives (Smithwick et al., 2002).

Regarding (2), deep volcanic Mazama ash soils in the vicinity of TC6/Crater Lake contain about 1/4 as much soil nitrogen as HJ Andrews sandy loam soils (Remillard, 1999).

We ran the LEMMA-initialized TC6 VELMA from 2010 to 2100 to examine initial amounts and long-term successional trajectories of live and dead forest biomass pools relevant to fuel load assessments developed for this study (Figure A.5-7). Although no U.S. Forest Service Forest Inventory and Analysis plots are located within the TC6 study area, published data describing observed biomass for mature ponderosa pine forests at the U.S. Forest Service Pringle Falls Experimental Forest are available to assess model performance.




g C/m$^2$ = grams of carbon per square meter; TC6 = Timber Crater 6; VELMA = Visualizing Ecosystem Land Management Assessments.

Also shown are modeled and observed biomass data for the HJ Andrews mature Douglas fir/western hemlock forest in western Oregon for which VELMA hydrological and biogeochemical parameters were calibrated (McKane et al., 2014; Abdelnour et al., 2013; Abdelnour et al., 2011) and only recently applied without changes to the TC6 site. See text for details.

**Figure A.5-7 Visualizing Ecosystem Land Management Assessments (VELMA) simulated biomass trajectories (2010 to 2100) for the Timber Crater 6 (TC6) case study site versus observed biomass for a mature eastern Oregon ponderosa pine forest [Pringle Falls Experimental Forest reference stand PF29; Smithwick et al. (2002)].**

Modeled TC6 biomass trajectories from 2010 to 2100 for stand-level foliage, live aboveground woody biomass, and dead aboveground woody biomass are in good agreement with long-term observed targets for mature ponderosa pine near Pringle Falls, OR. The TC6 and Pringle Falls forest sites are located on the same nutrient poor Mazama ash soil type, formed about 7,700 years ago when Mt. Mazama erupted, leading to the formation of Crater Lake.

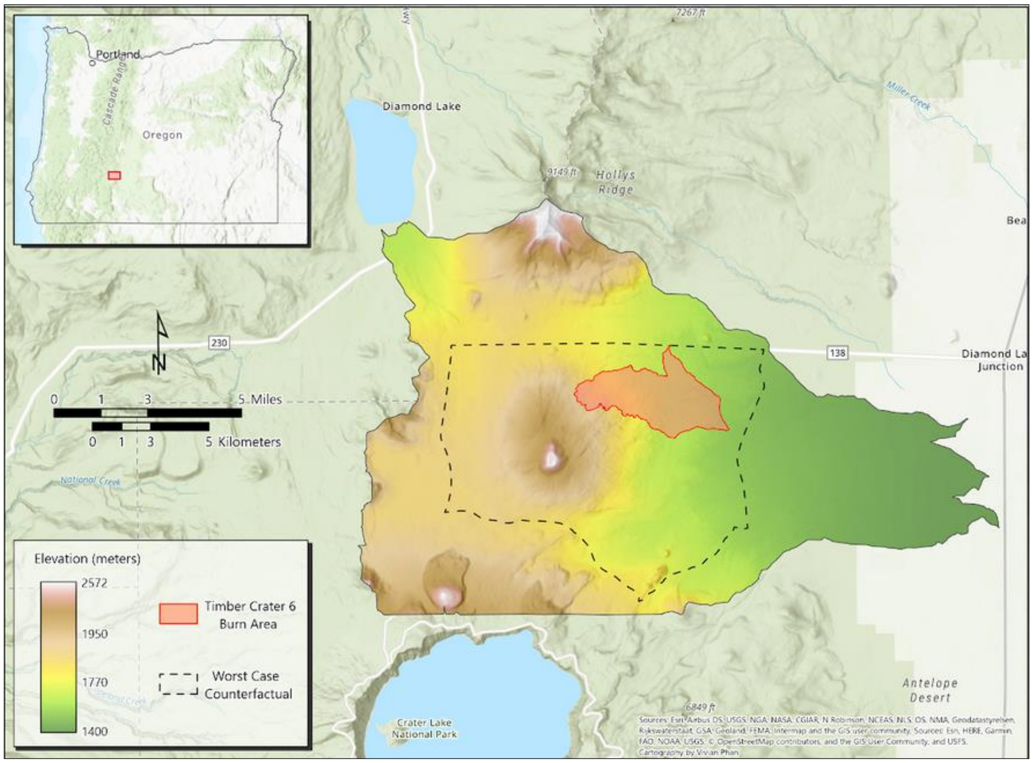
Also shown in Figure A.5-7 are modeled and observed biomass data for the HJ Andrews mature Douglas fir/western hemlock forest site (Watershed 10) for which VELMA hydrological and biogeochemical parameters were calibrated and applied to TC6. Taken together with the TC6 ponderosa pine results, Figure A.5-7 indicates that the limited availabilities of water and nutrients in eastern Oregon strongly constrain biomass growth and accumulation compared to conditions at the HJ Andrews site in western Oregon.

These results are encouraging for future VELMA applications, suggesting that it will be possible to use a single, broadly applicable set of VELMA parameters to closely approximate biomass and fuel load dynamics across large landscapes that include steep, complex gradients of climate, soil, vegetation, and disturbance histories. The availability of publicly-accessible spatial and temporal databases for all of these variables—with LEMMA annual 30-m forest biomass estimates going back to 1990—make such VELMA applications possible for essentially any forested site in California, Oregon, and Washington.

VELMA case study applications for the TC6, Rough, and Sheep Complex fires are discussed in the following sections.

#### A.5.2.4.1.3. Case Study 1: Timber Crater 6 (TC6)

VELMA simulations were conducted for the landscape surrounding the Timber Crater 6 Fire that occurred in south-central Oregon, near Crater Lake National Park, from July 21−26, 2018 (Figure A.5-8). The TC6 actual fire burned ~3,100 acres of forest cover dominated by mixed-age ponderosa pine and red fir. VELMA was used to simulate biomass/fuel loads for two main boundaries, including the actual TC6 burn area (red area in Figure A.5-8) and the worst-case hypothetical scenario (dotted line in Figure A.5-8).




FCCS = Fuel Characteristic Classification System; TC6 = Timber Crater 6; VELMA = Visualizing Environmental Land Management Assessments.

**Figure A.5-8 Study location of the actual Timber Crater 6 (TC6) Fire (red shaded area) and the maximum extent of hypothetical fire treatments, for which surface fuel load estimates were made by harmonizing products from both the Fuel Characteristic Classification System (FCCS) and the Visualizing Environmental Land Management Assessments (VELMA) model.**

As described in Section A.5.2.4.1.2, initial (time zero) aboveground total (live and dead) biomass estimates for the TC6 region were obtained from gradient nearest neighbor (GNN) forest biomass and species maps for 2010 from the Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) project at Oregon State University (Kennedy et al., 2018; Davis et al., 2015).

The total simulation area was divided into four separate areas due to the large spatial extent and since VELMA is a watershed model that depends on hydrologically created boundaries. Each of the four areas were simulated separately by VELMA and the results were subsequently stitched together to encapsulate the full fire boundary area. Each simulation began in 2009 to stabilize all pools prior to initialization. Spatially distributed biomass quantities from LEMMA were then incorporated on 2010 Julian Day 1. Each simulation was then conducted until 2020, but the relevant surface fuel loads for 2018 Julian Day 201 (July 20, 2018), which represent the day prior to the start of the TC6 fire, were used for subsequent analysis. Gridded inputs of elevation, land use/land cover, and soils were collected and rescaled to match the 30-m resolution of the FCCS/LANDFIRE vegetation cover data it was intended to supplement.

The study site digital elevation model (DEM) was clipped from the national elevation data set (NED) acquired from the U.S. Geological Survey (USGS) and rescaled from a 1/3 arc-second resolution to 30 m. The 30-m DEM was flat-processed using the JPDEM-Dredge processing tool (McKane et al., 2014; Pan et al., 2012). JPDEM was also used to derive the stream network based on existing elevation changes.

A single forest ecosystem calibration of VELMA was applied to TC6 that has been found to be broadly applicable to Pacific Northwest coniferous forest types, including the ponderosa pine ecoregion of eastern Oregon. Model initialization and validation details are described in Section A.5.2.4.1.2.

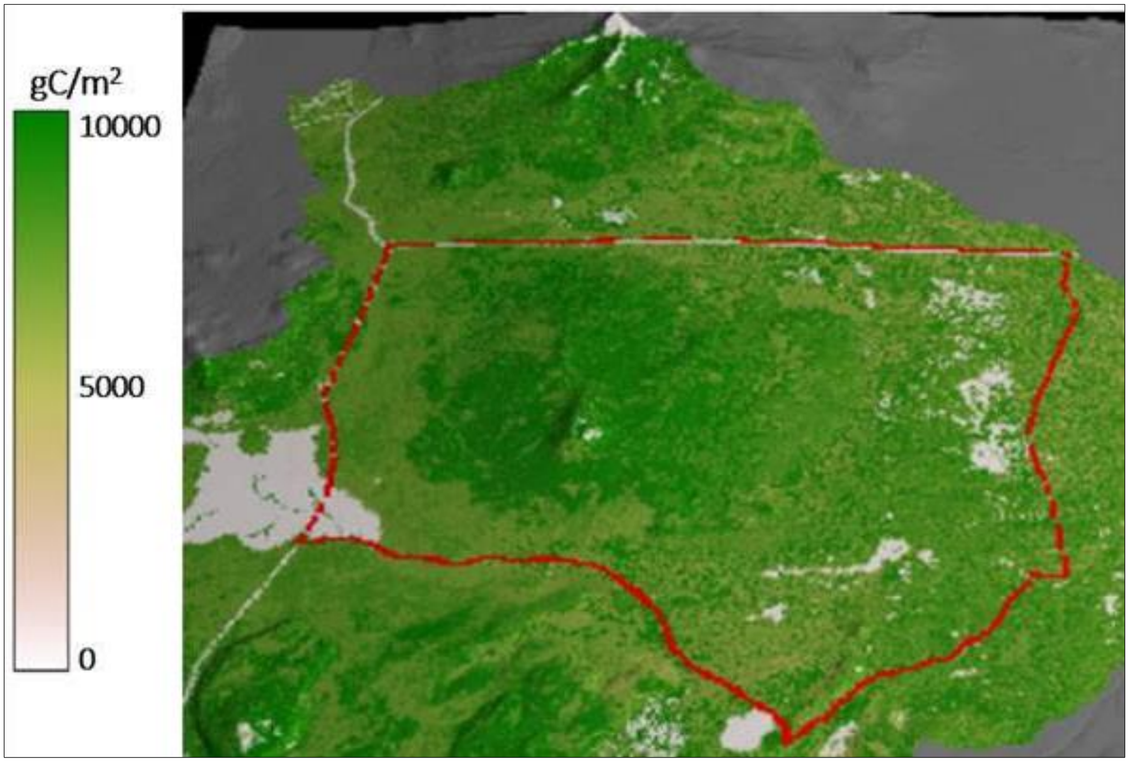
Daily precipitation and temperature drivers were obtained Oregon State University's PRISM Climate Group for 2010−2020 and consist of climatologically aided interpolation (CAI) values that use both long-term (30-year) averaging and radar measurements as inputs. For more information, see Daly et al. (2008) and https://prism.oregonstate.edu/explorer/. No stream flow data were available for hydrologic validation for this particular region. Nonetheless, VELMA's ability to model hydrologic processes with minimal calibration has been shown to be regionally robust (Figure A.5-6).

VELMA's simulation outputs include a suite of environmental parameters that can be used to model and better understand spatial and temporal variability in ecosystem properties that result from differences in climate, wildfire, management, and other disturbances. Responses modeled include changes in live and dead aboveground and belowground biomass components, stream flow, stream temperature, stream nutrients and contaminant, and others.

For this case study, VELMA was used to simulate aboveground live and dead biomass pools corresponding to fuel loadings for forest overstory trees (excluding near-surface fuels such as downed coarse woody debris, shrubs, etc. that are not easily detected using Landsat-based satellite technology such as LEMMA). These fuel categories were simulated at 30-m resolution and a daily time step. These spatial and temporal resolutions can be aggregated to lower resolutions using spatial and temporal averaging techniques.

Specifically, for the Timber Crater 6 application, VELMA's simulated aboveground live biomass pools, including stem and leaf components, were exported as 30-m raster data sets. These represent the aboveground live stem and leaf material across the TC6 region that are available on the day prior to the actual TC6 fire, that is, July 20, 2018. Model performance tests shown in Figure A.5-7 demonstrate VELMA's capabilities for accurately simulating aboveground biomass pools relevant to fuel load estimation purposes. Figure A.5-9 shows VELMA's aboveground biomass simulations for the worst-case hypothetical boundary associated with the TC6 fire.

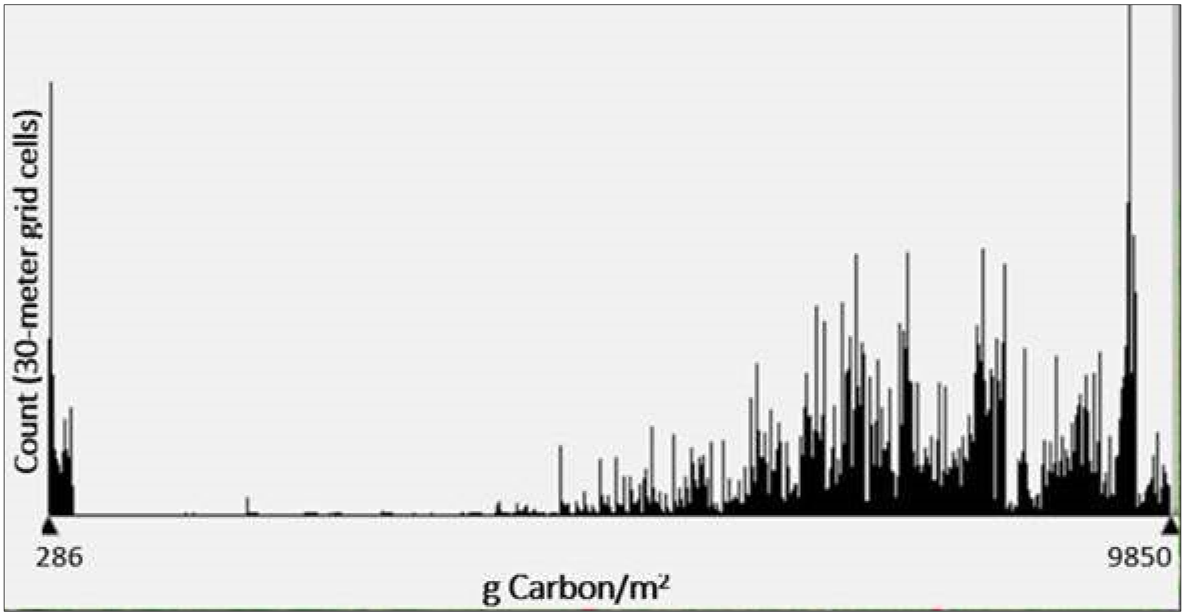
Figure A.5-10 is a histogram of aboveground stem values, which accounted for the majority of the total aboveground live biomass.




g C/m$^2$ = grams of carbon per square meter; FIA = Forest Inventory and Analysis; TC6 = Timber Crater 6; USFS = U.S. Forest Service; VELMA = Visualizing Ecosystem Land Management Assessments.

The red line is the simulation boundary for hypothetical TC6 worst-case BlueSky Pipeline modeling scenarios. Spatial variations in VELMA modeled aboveground biomass (g carbon/m$^2$) range from near zero (white shading) to a maximum of ~10,000 g carbon/m$^2$ (dark green), which corresponds to regional total biomass maxima for ponderosa/lodgepole pine-dominated forests measured on permanent plots maintained by the FIA network (USFS reference) and by the Pringle Falls Research Natural Area (Smithwick et al., 2002).

**Figure A.5-9 30-m resolution Visualizing Ecosystem Land Management Assessments (VELMA) aboveground live forest biomass results for the Timber Crater 6 (TC6) case study area for the day before the beginning of the actual TC6 fire on July 20, 2018 (see also Figure A.5-8).**




g Carbon/m$^2$ = grams of carbon per square meter; TC6 = Timber Crater 6; VELMA = Visualizing Ecosystem Land Management Assessments.

Vertical bars describe the number of 30-m grid cells for the range of biomass values shown on the *y*-axis. See Figure A.5-9 for worst-case scenario boundary.

**Figure A.5-10 Histogram of aboveground stem biomass simulated by Visualizing Ecosystem Land Management Assessments (VELMA) in the worst-case hypothetical scenario associated with the Timber Crater 6 (TC6) Fire (simulation day: July 20, 2018).**

Note that a regional maximum observed aboveground biomass of approximately 10,000 g C/m$^2$ has been reported by Smithwick et al. (2002) at the nearby Pringle Falls Research Natural Area. Data for this old-growth ponderosa pine forest was used to validate VELMA-simulated biomass in this study, as described in Section A.5.2.4.1.2. Figure A.5-9 shows that this maximum biomass estimate corresponds well with the western portion of the TC6 boundary, which are older and less disturbed. In fuel load terms, this is equivalent to 44.6 U.S. tons C/acre or 89.2 U.S. tons dry wt./acre.

These VELMA simulations were used to supplement the FCCS surface fuel load estimations for the TC6 region. The process by which the FCCS and VELMA data products were combined and exported to the BlueSky Pipeline suite of air quality models are described in Section A.5.2.4.1.5.

### A.5.2.4.1.4. Case Study 2: Rough, Sheep Complex, and Boulder Creek Fires

The second case study focused on the 2015 Rough Fire in the Sierra National Forest in California and consisted of a total of 151,000 burned acres (Figure A.5-11). In late August of that year, the fire expanded eastward, encountering areas partially burned in two earlier, less intense fires—the 2010 Sheep Complex wildfire and the 2013 Boulder Creek Prescribed Fire. These earlier fires mostly reduced surface fuels, likely preventing the speed and severity of the rapidly advancing Rough Fire in 2015, at least in those particular areas and points to the east (Figure A.5-11). A National Park Service interactive story map of the Rough Fire clearly illustrates these Rough Fire dynamics (https://www.nps.gov/seki/learn/nature/rough-fire-interactive-map.htm).

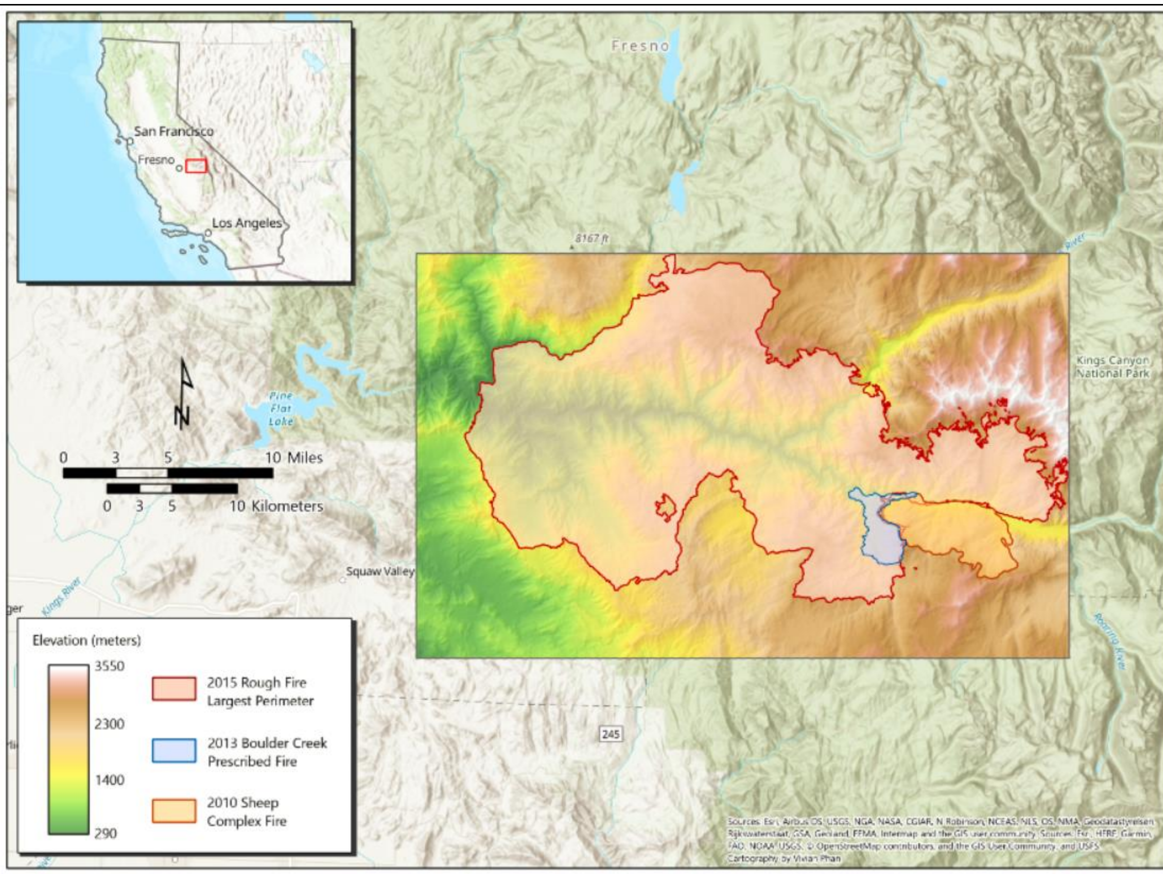



**Figure A.5-11 Study location of the 2015 Rough Fire, the 2010 Sheep Complex Fire, and the 2013 Boulder Creek Prescribed Fire.**

The fuelbed characterization objectives of this case study were to (1) use LEMMA and VELMA-based methods to augment and improve accuracies of existing FCCS surface fuel load estimates within the Rough, Sheep Complex, and Boulder Creek fire boundaries and (2) provide the combined VELMA-FCCS fuelbed data to the BlueSky Pipeline CONSUME fire simulator.

To accomplish this, similarly to the TC6 case study, aboveground forest biomass estimates for this case study were obtained from 30-m, satellite-derived forest biomass and species maps from the Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) project at Oregon State University (Kennedy et al., 2018; Davis et al., 2015; Kennedy et al., 2012).

LEMMA data for 2012 were obtained for the extent of the Rough Fire boundary, whereas LEMMA data for 2010 and 2013 were obtained for the Sheep Complex and Boulder Creek boundaries, respectively.

As described for the TC6 case study (Section A.5.2.4.1.3), these LEMMA data were processed through the VELMA Spatial_Pools_Py3_CommandLine.py Python tool that converted aboveground biomass from a single layer into VELMA's 13 plant and soil carbon and nitrogen pools, which include forest leaf biomass and aboveground stem wood (boles, branches, twigs) fuelbed categories.

The fuelbed data for aboveground stem and leaf biomass derived from this VELMA/LEMMA method were directly merged with FCCS fuelbed categories, skipping the multiyear VELMA biomass spin-up method applied to TC6. For TC6 there was a significant multiyear gap between the TC6 fire year (2018) and the closest year of available LEMMA data (2010), which necessitated an 8-year VELMA "spin-up" to account for growth and decay of live and dead biomass/fuelbeds during that time. Because there was a closer overall match between fire years and corresponding LEMMA data years for the Rough, Sheep Complex and Boulder Creek fires, it was not necessary to implement the VELMA spin-up step.

##### A.5.2.4.1.5. Process for Combining Fuel Characteristic Classification System (FCCS) and Visualizing Ecosystem Land Management Assessments (VELMA) Surface Fuel Load Estimations for All Case Studies

A depiction of the process used to conjoin the FCCS and VELMA data for all case studies is shown in Figure 5-6 from CHAPTER 5 of the Report. The process alters the original landscape units from FCCS to include new fuelbed categories that incorporate different VELMA-simulated aboveground biomass values. The CONSUME model within the BlueSky Pipeline is currently set up to accept inputs using a standard FCCS data format; therefore, VELMA's spatial raster data were processed and incorporated into the current FCCS data format to form a harmonized data product featuring spatially variable surface fuel loads.

VELMA's heterogeneous spatial maps of aboveground live stem and leaf biomass simulations were processed into categories, then spatially merged with the FCCS classes. These tasks were carried out in ArcGIS Pro and described below within the ESRI tool framework, though this data processing routine could be performed in most GIS software.

First, VELMA biomass data were reclassified into discrete bins based on their value using the "*Reclassify*" tool. The live aboveground stem and leaf biomass outputs were reclassified into 11 classes, as shown in Table A.5-3.

**Table A.5-3 Discrete bin classifications used for Visualizing Ecosystem Land Management Assessments (VELMA) and Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) aboveground biomass values for each of the case studies.**

| | Timber Crater 6 | | Rough and Sheep Complex | |
|---|---|---|---|---|
| Bin Numbers | Stem | Leaf | Stem | Leaf |
| 1 | 0−1,000 | 0−80 | 0−3,000 | 0−60 |
| 2 | 1,000−2,000 | 80−100 | 3,000−6,000 | 60−120 |
| 3 | 2,000−3,000 | 100−120 | 6,000−9,000 | 120−180 |
| 4 | 3,000−4,000 | 120−140 | 9,000−12,000 | 180−240 |
| 5 | 4,000−5,000 | 140−160 | 12,000−15,000 | 240−300 |
| 6 | 5,000−6,000 | 160−180 | 15,000−18,000 | 300−360 |
| 7 | 6,000−7,000 | 180−200 | 18,000−21,000 | 360−420 |
| 8 | 7,000−8,000 | 200−220 | 21,000−24,000 | 420−480 |
| 9 | 8,000−9,000 | 220−240 | 24,000−27,000 | 480−540 |
| 10 | 9,000−10,000 | 240−260 | 27,000−30,000 | 540−600 |
| 11 | 10,000−11,000 | 260−280 | 30,000−33,000 | 600−660 |

LEMMA = Landscape Ecology, Modeling, Mapping, and Analysis; VELMA = Visualizing Ecosystem Land Management Assessments.

Note: The average value in each bin range was used as the actual value in the raster.(grams carbon per meters squared).

Once the VELMA data were reclassified into discrete bins based on their values, the FCCS fuelbed identification raster was joined with the fuelbed loading look-up table that provided loadings for each of the fuelbed categories using "*Add Join*". Then, both the VELMA outputs and the FCCS data were joined together using "*Intersect* (Analysis)" after first converting to polygons using "*Raster to Polygon* (Conversion)." The resulting output provides a combined polygon file with the attribute table containing both sets of data in a spatially merged representation. The combined VELMA + FCCS polygon layer was then converted back to a raster using the "*Polygon to Raster* (Conversion)" and exported as a final raster layer, plus the tabular data was saved as an Excel file (.xlsx) using "*Table to Excel*."

While the raster file was now ready to be sent to CONSUME and the BlueSky Pipeline, a number of processing steps were needed to adjust the exported attribute table so that VELMA information replaced FCCS data for particular fuelbed categories and that the table followed the appropriate format. At this step, care was taken to ensure that the units supplied by VELMA were correctly converted to those used in FCCS. In particular, VELMA simulates aboveground biomass values as g C/m$^2$, whereas FCCS uses U.S. tons/acre and assumes dry weight biomass. Therefore, we conducted the conversion using the relationship 1 g C/m$^2$ = 0.0044609 U.S. tons/acre. That value was derived from 1 g = 1.10231 × 10$^{-6}$ U.S. ton and 1 m$^2$ = 0.000247105 acre. Alternatively, one can specify that 1 U.S. ton = 907,185 g and 1 acre = 4,046.86 m$^2$. These tons of carbon then were converted to tons of dry weight biomass by assuming that 0.5 g carbon are present in 1 g of dry weight biomass.

In addition, an R software (R Core Team, 2019) processing script was used to convert VELMA's total aboveground biomass estimates (live stem and leaf) to the appropriate quantity to replace fuel load defaults in FCCS.

Note that only forested fuelbeds were replaced using VELMA's simulated data, whereas all grassland and savanna fuelbeds continued to use the standard FCCS inputs. Parameters and equations from Jenkins et al. (2003) were used to derive component ratios for tree crowns for both hardwood and softwood species, and these ratios were multiplied by the VELMA's total aboveground biomass for each of the forested fuelbed classifications to replace the default FCCS "overstory_loading" category. The "midstory_loading" and "understory_loading" categories were set to zero during replacement to avoid double counting. All remaining fuelbed categories (e.g., snags, shrubs, litter, duff) continued to use FCCS default values.

The final outputs of combining FCCS and VELMA data to provide surface fuel loads to the CONSUME model in the BlueSky Pipeline consisted of two data products. The first was a new FCCS + VELMA raster file that included new unique fuelbed identification numbers. These fuelbeds incorporate both FCCS cover type specifications and VELMA's discrete biomass bins. The second data product was a revised fuel loading look-up table that is used to specify loadings for each of the fuelbed categories given in the raster. Both outputs can be found here: file://aa/ord/ORD/DATA/PRIV/CPHEA_WFLC_Report_Materials/VELMA%20Output/.

### A.5.2.5. Results

As mentioned in the previous methods section, the final outputs that combine FCCS and VELMA data were used as inputs to the CONSUME model in the BlueSky Pipeline. Note that while FCCS provides a number of fuel load categories for surface fuel loads (see Figure A.5-2), VELMA is used only to modify the crown loading estimates for forested cover types. An in-depth comparison of the resulting fuel loading changes is shown for each of the case studies in the following sections.

#### A.5.2.5.1. Case Study 1: Timber Crater 6 (TC6)

A comparison of the VELMA and FCCS crown loading estimates for all FCCS forested fuelbeds that represent greater than 1% of the total TC6 actual fire boundary are shown in Table A.5-4. Note that the VELMA values shown in the table are averages across all cells that have the FCCS fuelbed name. VELMA's simulations tend to be generally higher than those from FCCS, where, for example, VELMA predicts 15.28 U.S. tons/acre of overstory crown loading and FCCS predicts 9.51 U.S. tons/acre. An exception is the red fir forest, for which FCCS estimates a loading of 24.97 U.S. tons/acre and VELMA estimates an average value of 14.86 U.S. tons/acre.

Also, it is apparent that VELMA's simulated values are much greater than FCCS values for fuelbeds characterized by prior disturbance—that is, fuelbeds denoted with "WF 5-10 YR." FCCS data were obtained from 2012 and so these disturbance categories represent disturbances that occurred between 2002 and 2007, which therefore may underestimate the actual biomass present during the TC6 fire in 2018.

**Table A.5-4 Comparison of Timber Crater 6 (TC6) study domain crown loading estimates between Fuel Characteristic Classification System (FCCS) and Visualizing Ecosystem Land Management Assessments (VELMA) for all FCCS forested fuelbeds that represent greater than 1% of the total boundary area percentage.**

| FCCS Fuelbed Name | FCCS* | VELMA* | Area (%) |
|---|---|---|---|
| Pacific Ponderosa Pine Forest | 9.51 | 15.28 | 26 |
| Red Fir Forest | 24.97 | 14.86 | 15 |
| Red Fir-Mountain Hemlock-Lodgepole Pine-Western White Pine Forest | 16.21 | 16.11 | 9 |
| Giant Sequoia—White Fir—Sugar Pine Forest | 9.36 | 14.43 | 5 |
| WF 5−10 yr: Red Fir Forest | 4.37 | 14.98 | 4 |
| Pacific Silver Fir-Mountain Hemlock Forest | 9.38 | 16.00 | 3 |
| WF 5−10 yr: Giant Sequoia—White Fir—Sugar Pine Forest | 0.00 | 14.59 | 3 |
| Mature Lodgepole Pine Forest | 4.13 | 19.07 | 3 |
| WF 5−10yr**:** Pacific Ponderosa Pine Forest | 1.48 | 16.54 | 3 |
| Pacific Silver Fir-Sitka Alder Forest | 2.33 | 17.94 | 2 |
| Ponderosa Pine—Jeffrey Pine Forest | 8.62 | 14.71 | 1 |

FCCS = Fuel Characteristic Classification System; TC6 = Timber Crater 6; VELMA = Visualizing Ecosystem Land Management Assessments.

Note: The VELMA values represent the crown fuel loads estimated from VELMA's aboveground biomass simulations and Jenkins Et Al. (2003) tree component ratios, while the FCCS values are the sum of the "overstory_loading," "midstory_loading," and "understory_loading" fuel load categories. all units are provided in U.S. tons/acre dry weight biomass.

### A.5.2.5.2. Case Study 2: Sheep Complex and Rough Fires

A comparison of the FCCS and LEMMA crown loading estimates for all FCCS forested fuelbeds that represent greater than 1% of the total Sheep Complex actual fire boundary are shown in Table A.5-5.

Note that LEMMA data were only produced for a subset of the total number of fuelbeds due to lack of data of the component ratios available from Jenkins et al. (2003) that coincide with the FCCS fuelbed names depicted in the table. When available, these ratios were multiplied by LEMMA's total aboveground biomass for each of the forested fuelbed classifications to replace the default FCCS category, as described previously. As with the TC6 case study, the VELMA/LEMMA crown loading values are lower than the default FCCS values for Red Fir Forest fuelbed type (17.69 vs. 24.97 U.S. tons/acre, respectively), whereas they match well for the ponderosa (8.61 vs. and 8.62 U.S. tons/acre) Jeffrey Pine (8.13 vs. 8.33 U.S. tons/acre) mixes and are greater than the FCCS defaults for the Mature Lodgepole Pine Forest type (18.25 vs. 4.13 U.S. tons/acre).

For the Rough Fire boundary, a comparison of the VELMA and FCCS crown loading estimates for all FCCS forested fuelbeds that represent greater than 1% of the fire boundary are shown in Table A.5-6.

**Table A.5-5 Comparison of Sheep Complex study domain crown loading estimates between Fuel Characteristic Classification System (FCCS) and Visualizing Ecosystem Land Management Assessments (VELMA)/Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) for all FCCS forested fuelbeds that represent greater than 1% of the total Sheep Complex boundary area percentage.**

| FCCS Fuelbed Name | FCCS | VELMA/LEMMA | Area (%) |
|---|---|---|---|
| Red Fir Forest | 24.97 | 17.69 | 18 |
| California Black Oak Woodland | 19.63 | | 14 |
| Douglas Fir-Sugar Pine-Tanoak Forest | 19.30 | | 12 |
| Ponderosa Pine-Jeffrey Pine Forest | 8.62 | 8.61 | 3 |
| Douglas Fir-White Fir Forest | 20.94 | | 3 |
| Jeffrey Pine-Red Fir-White Fir/Greenleaf-Snowbrush Forest | 14.38 | | 3 |
| Jeffrey Pine-Ponderosa Pine-Douglas Fir-California Black Oak Forest | 8.33 | 8.13 | 2 |
| Mature Lodgepole Pine Forest | 4.13 | 18.25 | 2 |
| Douglas Fir/Ceanothus Forest | 3.75 | | 2 |
| Subalpine Fir-Lodgepole Pine-Whitebark Pine-Engelmann Spruce Forest | 9.55 | | 1 |

FCCS = Fuel Characteristic Classification System; LEMMA = Landscape Ecology, Modeling, Mapping, and Analysis; VELMA = Visualizing Ecosystem Land Management Assessments.

Note: That tree component ratios used by Jenkins et al. (2003) were unavailable for some FCCS fuelbed cover types, and therefore crown loading values could not be computed and are shown as blanks.

*The LEMMA values represent the crown fuel loads estimated from LEMMA's aboveground biomass estimates and Jenkins et al. (2003) tree component ratios, while the FCCS values are the sum of the "overstory_loading," "midstory_loading," and "understory_loading" fuel load categories. All units are provided in U.S. tons/acre dry weight biomass.

**Table A.5-6 Comparison of Rough study domain crown loading estimates between Fuel Characteristic Classification System (FCCS) and Visualizing Ecosystem Land Management Assessments (VELMA)/Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) for all FCCS forested fuelbeds that represent greater than 1% of the total Rough Fire area percentage.**

| Fuelbed Name | FCCS | VELMA/LEMMA | Area (%) |
|---|---|---|---|
| California Black Oak Woodland | 19.63 | | 18 |
| California Live Oak-Blue Oak Woodland | 1.21 | | 17 |
| Douglas Fir-Sugar Pine-Tanoak Forest | 19.30 | | 17 |
| Red Fir Forest | 24.97 | 18.68 | 15 |
| Jeffrey Pine-Ponderosa Pine-Douglas Fir-California Black Oak Forest | 8.33 | 13.18 | 4 |
| Jeffrey Pine-Red Fir-White Fir/Greenleaf-Snowbrush Forest | 14.38 | | 3 |
| Douglas Fir-White Fir Forest | 20.94 | | 2 |
| Ponderosa Pine-Jeffrey Pine Forest | 8.62 | 13.59 | 2 |
| Subalpine Fir-Lodgepole Pine-Whitebark Pine-Engelmann Spruce Forest | 9.55 | | 2 |
| Mature Lodgepole Pine Forest | 4.13 | 19.43 | 2 |
| Douglas Fir/Ceanothus Forest | 3.75 | | 1 |
| Black Cottonwood-Douglas Fir-Quaking Aspen Forest | 28.68 | | 1 |

FCCS = Fuel Characteristic Classification System; LEMMA = Landscape Ecology, Modeling, Mapping, and Analysis; VELMA = Visualizing Ecosystem Land Management Assessments.

LEMMA data were only updated for some cover types due to data availability for converting total aboveground biomass estimates to crown loadings using equations from Jenkins et al. (2003).

The LEMMA values represent the crown fuel loads estimated from LEMMA's aboveground biomass estimates and Jenkins et al. (2003) tree component ratios, while the FCCS values are the sum of the "overstory_loading," "midstory_loading," and "understory_loading" fuel load categories. All units are provided in U.S. tons/acre dry weight biomass.

As expected based on the previous case studies, VELMA estimates lower crown loading values compared with the default FCCS values for Red Fir Forest. However, the remainder of comparisons show that VELMA/LEMMA estimate higher crown loading values compared with the FCCS defaults. Further validation is needed to confirm the canopy estimations from VELMA/LEMMA and their comparison with the original estimates performed by FCCS. Also, note that the values in Table A.5-4, Table A.5-5, and Table A.5-6 represent spatial averages of VELMA data for given FCCS cover types to simplify direct comparison. The combined FCCS/VELMA data products sent to the BlueSky Pipeline, however, include spatially distributed crown loading estimates that are not fully reflected in the previous tables.

### A.5.2.6. Conclusions

The use of vegetation-based fuel load classification systems can be extremely helpful for air quality modelers to simulate the air quality impacts of historical or projected wildfires. However, these classification systems are inherently crafted to represent a wide variety of fuel loads across the entire U.S. and therefore do not always capture the fine spatial and temporal heterogeneity associated with landscape-level fuel load changes or disturbance patterns. In this study, we used a spatially distributed ecohydrological landscape model (VELMA) to simulate aboveground live biomass and supplement existing fuel load characterization data for the Timber Crater 6, Rough, Sheep Complex and Boulder Creek fire boundaries. VELMA was initialized using LEMMA data that provided spatially distributed estimates of live aboveground biomass corresponding to the regions of each of the case studies.

As shown in Figure A.5-7 and Figure A.5-9, VELMA fuel load estimates compare well with measured data describing upper limits of aboveground biomass for ponderosa pine stands in eastern Oregon (Smithwick et al., 2002). In addition, VELMA crown loading estimates for forested fuelbeds were compared with FCCS default values.

While differences exist between VELMA and default FCCS estimates for forest crowns and other fuelbeds, further assessments of these estimates based on observed data would be beneficial to examine the validity of surface fuel loads within the regional domain of this study.

Discussions with project partners and others familiar with the case study sites have so far turned up no available georeferenced forest biomass data for assessing the accuracy of model-based estimates for the case study sites. For example, there exists high-quality biomass data for Forest Inventory and Analysis plots within the Rough Fire boundary, but precise coordinates for these plots are inaccessible for security reasons.

Those challenges notwithstanding, it is important to emphasize that the ability of VELMA to accurately simulate ecosystem responses across western and eastern Oregon using a single set of model equations and parameter values provides the strongest possible test of a process-based modeling framework (Section A.5.2.4.1.2). In essence, VELMA behaves similarly, though imperfectly, to real ecosystems with regard to changes in structure and function in response to environmental changes, whether in situ or across landscape gradients.

These results are encouraging for future VELMA applications, suggesting that it will be possible to closely approximate biomass and fuel load dynamics across large landscapes that include steep, complex gradients of climate, soil, vegetation, and disturbance histories. The availability of publicly-accessible spatial and temporal databases for all of these variables—including LEMMA annual 30-m forest biomass estimates going back to 1990—make such VELMA applications possible for essentially any forested site within some western states most hard hit by recent wildfires—California, Oregon, and Washington.

Finally, VELMA is already capable of simulating real and hypothetical land management practices and other disturbances (harvests, wild and prescribed fires, extreme climate events, etc.) at multiple spatial scales. Therefore, future research could incorporate simulations of alternative prescribed burning and mechanical thinning practices to explore local and regional impacts on fuel loads and consequent air quality impacts. Additionally, since VELMA is designed to simulate ecohydrological processes, it can also be used to assess effects of wild and prescribed fires on water quality and quantity, thereby providing an opportunity for integrated air and water quality impact assessments on human health.

# A.6. SUPPLEMENTAL INFORMATION FOR CHAPTER 6

1

## A.6.1. Supplemental Information for Section 6.2

**Table A.6-1 Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| *ED Visits and Hospital Admissions; Medication Use* | | | | |
| Alman et al. (2016); Colorado; 2012 Wildfires (6/5/12−7/6/12) | ED Visits: asthma and wheeze, URI, pneumonia, bronchitis, COPD, RESPIRATORY disease, AMI, IHD, dysrhythmia, CHF, ischemic stroke, PVD, CVD (All; 0−18; 19−64; 65+) | $PM_{2.5}$ (24-h avg; 1-h max) | Modeled | WRF-Chem used to estimate $PM_{2.5}$ concentrations at 12 × 12 km grid cells. Addresses for each patient geocoded and assigned $PM_{2.5}$ concentration from respective grid cell. Model evaluation: Model absolute bias (i.e., average difference between model and monitored $PM_{2.5}$ concentrations), 13 µg/m$^3$ for six monitoring stations around Denver Metro Area, 13 µg/m$^3$ for two stations north-east of Denver, and 19 µg/m$^3$ for the station east of Denver. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| DeFlorio-Barker et al. (2019);<br>692 U.S. counties within 200 km of 123 large fires;<br>>10,000 acres burned<br>(2008−2010) | HA: respiratory; asthma, bronchitis and wheezing; all CVD<br>(65+) | $PM_{2.5}$ TotCMAQ; $PM_{2.5}$ Tot; $PM_{2.5}$ TotCMAQ-M<br>(24-h avg) | Monitored<br>Modeled | (1) Ambient $PM_{2.5}$ from monitoring stations (>4,000), resulting in county-wide averages available for 178 of 692 counties; (2) $PM_{2.5}$ estimated using CMAQ. CMAQ estimated $PM_{2.5}$ at 12 × 12 km grid cells—estimated $PM_{2.5}$ with all emissions ($PM_{2.5}$ TotCMAQ) and without wildfire (CMAQ NFCMAQ). CMAQ data used to calculate area-weighted $PM_{2.5}$ estimates for each county. Difference between CMAQ estimates represented fire-specific $PM_{2.5}$ concentrations ($PM_{2.5}$ FCMAQ). SmokeDay = $PM_{2.5}$ FCMAQ > 5 µg/$m^3$. |
| Delfino et al. (2009);<br>Southern California;<br>2003 Wildfires<br>(Total: 10/1/03−11/15/03; Prefire: 10/1−10/2; Fire: 10/21−10/30; Post-fire: 10/31−11/15) | HA: All respiratory, asthma, acute bronchitis, COPD, pneumonia, all CVD, IHD, CHF, dysrhythmia, cerebrovascular and stroke<br>(All; 0−4; 5−19; 20−64; 65−99) | $PM_{2.5}$<br>(24-h avg) | Monitored | Combination of monitoring data, continuous hourly PM data at colocated or closely located sites, and light extinction from visibility data. Meteorological conditions and smoke data from MODIS at 250-m resolution. For smoke periods created polygons from smoke-covered areas and measured or estimated $PM_{2.5}$ concentrations from predictive models to assign exposures at ZIP code centroid. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Gan et al. (2017);<br>Washington;<br>2012 Wildfires<br>(7/1/12−10/31/12) | HA: All respiratory, asthma, COPD, pneumonia, acute bronchitis, CVD, arrhythmia, cerebrovascular disease, HF, IHD, MI<br>(All; <15; 15−65; 65+) | Smoke $PM_{2.5}$<br>(24-h avg) | Modeled<br>Satellite | (1) WRF-Chem: Estimated daily $PM_{2.5}$ at 15 × 15 km grid cell, ran additional simulations with biomass burning emissions turned off to estimate nonwildfire smoke $PM_{2.5}$.<br>Model evaluation: Slope = 0.67, $R^2$ = 0.25<br>(2) Kriging in situ surface monitors: Interpolated monitoring data (212 monitors) to 15 × 15 km grid cells.<br>Model evaluation: Slope = 0.70, $R^2$ = 0.69<br>(3) GWR: estimated $PM_{2.5}$ concentrations at 15 × 15 km grid cells by combining kriged, AOD, and WRF-CHEM estimates.<br>Model evaluation: Slope = 0.78; $R^2$ = 0.66.<br>To distinguish wildfire $PM_{2.5}$ for WRF-Chem subtracted out nonsmoke $PM_{2.5}$ produced by WRF-Chem. For kriging and GWR methods estimated background $PM_{2.5}$ using NOAAs HMS to identify days where wildfire smoke not near a monitor. Smoke plumes in HMS accompanied by estimated $PM_{2.5}$ concentrations from atmospheric models. Calculated median $PM_{2.5}$ concentration for each monitor on nonfire days, these concentrations were interpolated by kriging for each grid cell. These nonfire $PM_{2.5}$ concentrations were subtracted from $PM_{2.5}$ concentrations for each method to estimate $PM_{2.5}$ attributed to smoke. |
| Gan et al. (2020);<br>Oregon;<br>Douglas Complex Fire<br>Big Windy Complex Fire<br>(5/1/13−9/30/13) | HA: Asthma<br>Medication use: Short-acting β2 agonists (SABA) pharmacy refills<br>(All; <15; 15−65; 65+) | Smoke $PM_{2.5}$<br>(24-h avg) | Modeled<br>Satellite | Similar method as Gan et al. (2017), focusing only on the GWR method. estimated $PM_{2.5}$ concentrations at 15 × 15 km grid cells by combining kriged, AOD, and WRF-CHEM estimates. Monitors used in the analysis consisted of both FRM and FEM monitors. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Hutchinson et al. (2018); San Diego, CA; 2007 Wildfires (9/1/07−11/29/07) | ED Visits: Respiratory index, Asthma (0−64) | Wildfire $PM_{2.5}$ (24-h avg) | Modeled | Wildfire Emissions from WFEIS were used in HYSPLIT to estimate wildfire $PM_{2.5}$ concentrations at 0.01° grid on an hourly basis. 24-h avg concentrations calculated at the ZIP code level. |
| Leibel et al. (2020); San Diego County, CA; Lilac Fire (2011−2017; Fire: 12/6/17−12/17/17) | ED Visits and Urgent care visits: All respiratory (0−19) | $PM_{2.5}$ (24-h avg) | Monitored | 24-h avg $PM_{2.5}$ concentrations from 10 fixed site monitors. $PM_{2.5}$ concentrations interpolated using inverse distance interpolation model using stations within 12 miles from each population weighted ZIP code centroid, concentrations than averaged and assigned to each ZIP code. Monitors closest to each centroid were given greater weight (weighted using squared inverse distance). |
| Liu et al. (2017a); 561 Western U.S. counties; Wildfire season (May−October, 2004−2009) | HA: All respiratory, All CVD (65+) | Wildfire $PM_{2.5}$; smoke wave day vs. nonsmoke wave day | Monitored Modeled | GEOS-Chem predictions of “all-source $PM_{2.5}$” and “no-fire $PM_{2.5}$” to ~50 × 75 km grid cell. Ground based or aircraft measurements used to validate model results. Area weighted averaging used to convert gridded predictions to county-level averages. GEOS-Chem predictions biased low during extreme events so model calibrated using county-average monitoring data. Smoke wave defined as 2+ consecutive days of wildfire $PM_{2.5}$ > 20 µg/m$^3$ (98th percentile, sensitivity analyses focusing on 23 µg/m$^3$ [98.5 percentile], 28 µg/m$^3$ [99th percentile], and 37 µg/m$^3$ [99.5 percentile]). |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| (Liu et al., 2017b);<br>561 western U.S. counties;<br>Wildfire season<br>(May−October, 2004−2009) | HA: Respiratory (COPD and respiratory tract infections)<br>(65−75; 75−84; 85+) | Wildfire $PM_{2.5}$; smoke wave day vs. nonsmoke wave day | Monitored<br>Modeled | GEOS-Chem predictions of “all-source $PM_{2.5}$” and “no-fire $PM_{2.5}$” to ~50 × 75 km grid cell. Ground based or aircraft measurements used to validate model results. Area weighted averaging used to convert gridded predictions to county-level averages. GEOS-Chem predictions biased low during extreme events so model calibrated using county-average monitoring data. Smoke wave defined as 2+ consecutive days of wildfire $PM_{2.5}$ > 37 µg/m$^3$ (99.5%). |
| Rappold et al. (2011);<br>42 North Carolina counties<br>Peet Fire in Pocosin Lakes National Wildlife Refuge;<br>(6/1/08−7/14/08) | ED Visits: All respiratory, COPD, pneumonia and acute bronchitis, URIs, all CVD, MI, HF, dysrhythmia, respiratory/other chest pain symptoms<br>(All; <65; 65+) | Smoke plume | Satellite | Half hour, AOD at 4 × 4 km averaged over daytime hours to assign county-level exposure. AOD ≥ 1.25 classified as high-density plume. Counties where at least 25% of geographic area of county exceeded AOD threshold were categorized as high-exposure window. Counties with smoke exposure on at least 2 days classified as exposed (18 counties); 23 referent counties (15 exposed 1 day; 8 <1 day). |
| Rappold et al. (2012);<br>40 North Carolina counties<br>Peet Fire in Pocosin Lakes National Wildlife Refuge;<br>(6/1/08−7/14/08) | ED visits: asthma, CHF<br>(>18; >44) | Wildfire $PM_{2.5}$<br>(24-h avg) | Modeled<br>Satellite | $PM_{2.5}$ concentrations obtained from NOAA SFS. $PM_{2.5}$ concentrations based on smoke dispersion simulations from HYSPLIT, which relies on satellite information of wildfire location. Hourly $PM_{2.5}$ concentrations at 0.15 × 0.15° (~13.5 km) estimated a lowest 100 m surface area averaged to generate 24-h avg concentrations. Daily averages for each county calculated over county boundaries using Monte Carlo approximation. HYSPLIT data not available for 6/4, underestimating concentrations on that day. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Reid et al. (2016);<br>Northern California, 781 ZCTA<br>(Air Basins: Sacramento Valley, San Francisco Bay Area, Mountain Counties, Lake County, North Central Coast, northern part of San Joaquin Valley)<br>Thousands of wildfires from lightning strikes June 20−21, located in Trinity Alps, Sierra NV and Big Sur;<br>(Prefire: 5/6/08−6/19/08; Fire: 6/20/08−7/31/08; Post-fire: 8/1/08−9/15/08) | ED visits and HAs: All respiratory, asthma, COPD, pneumonia, all CVD, IHD, CHF, dysrhythmias, hypertension, cerebrovascular disease<br>(All; <20; 65+) | $PM_{2.5}$<br>(24-h avg) | Monitored<br>Modeled<br>Satellite | Data-adaptive machine learning employing 10-fold CV. Used data from 112 monitoring stations as dependent variable and predictor variables included AOD from GEOS, WRF-Chem model output, various meterological variables, Julian date, weekend, land use types within 1 km, *X* and *Y* coordinates, elevation, and traffic counts. Used GBM with six most predictive variables for the main model. Estimated exposures at population-weighted centroid of 781 ZCTA.<br>Model evaluation: CV-$R^2$ = 0.78, CV-RMSE = 1.46 $\mu g/m^3$ |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Reid et al. (2019);<br>Northern California, 753 ZIP codes (Air Basins: Sacramento Valley, San Francisco Bay Area, Mountain Counties, Lake County, North Central Coast, northern part of San Joaquin Valley);<br>Thousands of wildfires from lightning strikes June 20−21, located in Trinity Alps, Sierra, NV and Big Sur<br>(5/6/08−9/26/08) | ED visits: All respiratory, asthma, COPD, pneumonia, acute bronchitis, acute respiratory infections<br>(All) | $PM_{2.5}$<br>(24-h avg)<br>$O_3$<br>(8-h max) | Monitored<br>Modeled<br>Satellite | Used exposure model detailed in Reid et al. (2016). Data-adaptive machine learning employing 10-fold CV. Used data from 112 monitoring stations as dependent variable and predictor variables included AOD from GEOS, WRF-Chem model output, various meterological variables, Julian date, weekend, land use types within 1 km, *X* and *Y* coordinates, elevation and traffic counts. Used GBM with six most predictive variables for the main model. Estimated exposures at each ZIP code centroid.<br>Model evaluation: For $PM_{2.5}$, CV-$R^2$ = 0.78, CV-RMSE = 1.46 µg/m$^3$. For $O_3$, CV-$R^2$ = 0.83 |
| Stowell et al. (2019);<br>Colorado;<br>Wildfire season<br>(April−September, 2011−2014) | ED visits and HAs: all respiratory, asthma COPD, URIs. bronchitis, IHD, AMI, CHF, dysrhythmia, peripherial/cerebrovasular disease, all CVD<br>(All; 0−18; 19−64; 65+) | Smoke $PM_{2.5}$ | Monitored<br>Modeled<br>Satellite | Two model approach where data combined from AOD from MAIAC, model simulations from CMAQ, and ground based $PM_{2.5}$ measurements. Model 1, used random forest modeling to incorporate AOD data, smoke mask, meterological fields, and land-use variables. Second model used statistical downscaling to calibrate CMAQ $PM_{2.5}$ predictions. Exposure data at 1 × 1 km grid cell. To estimate wildfire smoke $PM_{2.5}$, CMAQ scenarios with and without smoke and dust particles. Difference between scenarios divided by total $PM_{2.5}$ to obtain smoke fraction which was multiplied by total satellite-based $PM_{2.5}$ to obtain smoke $PM_{2.5}$ concentrations.<br>Model evaluation: For CMAQ predictions, CV-$R^2$ = 0.81; RMSE = 1.85 µg/m. Random forest model improved $R^2$ from 0.65 to 0.92. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Tinling et al. (2016);<br>28 North Carolina counties with at least one 24-h avg smoke $PM_{2.5}$ concentration > 20 μg/m$^3$;<br>Pains Bay Fire<br>(5/5/11−6/19/11) | ED visits: Respiratory/other chest symptoms, all respiratory, asthma, COPD, URI, All CVD, dysrhythmia, HF, hypertension<br>(All; <18; 18−64; 65+) | Wildfire $PM_{2.5}$ | Modeled | County-level daily wildfire $PM_{2.5}$ estimated from modeled predictions from NOAA SFS. |
| Wettstein et al. (2018);<br>Eight California Air Basins<br>(Great Basin Valleys, Lake County, Lake Tahoe, Mountain Counties, North Coast, Northeast Plateau, Sacramento Valley, San Joaquin Valley);<br>2015 Wildfire season<br>(May−September, 2015) | ED visits: All CV, hypertension, IHD, MI, dysrhythmia, HF, PE, All cerebrovascular, ischemic stroke, TIA, all respiratory<br>(19+; 45−64; 65+) | Smoke density | Modeled | Smoke plume data from NOAA HMS, assigning daily maximum density to each ZIP code based off estimated $PM_{2.5}$ concentration data where concentrations within the range of 0−10 μg/m$^3$ defined as light , 10.5−21.5 μg/m$^3$ defined as medium , and 22+ μg/m$^3$ defined as dense. |
| *Out-of-Hospital Evidents* | | | | |
| Jones et al. (2020);<br>14 California counties;<br>Wildfires ≥50,000 acres burned or ≥50 days long<br>(May−October, 2015−2017) | OHCA<br>(19+) | Smoke day | Modeled | NOAA HMS used to detect plumes using visual range of satellite images and assigned estimated smoke $PM_{2.5}$ density: light (0−10 μg/m$^3$); medium (10.5−21.5 μg/m$^3$); and heavy (>22 μg/m$^3$). Used geospatial intersect function to assign smoke data at the census block group and then aggregated to census tract, maximum smoke density used to define exposure. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| *Mortality* | | | | |
| Doubleday et al. (2020); Washington; Wildfire season (June−September, 2006−2017) | Total (nonaccidental), cardiovascular, IHD, respiratory, asthma, COPD, pneumonia, cerebrovascular (All) | Smoke day vs. nonsmoke day | Monitored Modeled | 4 × 4 km grid cells from AIRACT-4, each grid cell assigned to 1 of 3 AQ monitors closest to each grid cell out of 75 monitors in Washington. Grid cells matched to nearby monitors based on agreement between interpolated and monitored $PM_{2.5}$. Each grid cell then assigned the daily $PM_{2.5}$ monitor concentration. Smoke day defined as days with $PM_{2.5}$ monitor concentrations > 20.4 µg/m$^3$, with additional criteria if $PM_{2.5}$ concentrations between 9 and 20.4 µg/m$^3$: (1: 2 of 3 days > 9 µg/m$^3$; 2: 1 day > 15 µg/m$^3$; 3: for urban areas at least 50% monitors > 9 µg/m$^3$). |
| Xi et al. (2020); 253 U.S. Counties; (2008−2012) | All-cause, cardiac, vascular, infection, other (50+) | Wildfire $PM_{2.5}$ | Modeled | Ambient $PM_{2.5}$ concentrations were predicted at 12 × 12 km grid cells using CMAQ with and without wildland fire emissions. The difference between the with and without wildland fire emissions represented wildfire-specific $PM_{2.5}$. Hourly concentrations were averaged to calculate a daily county-level 24-h avg $PM_{2.5}$ concentration. |

**Table A.6-1 (Continued): Study-specific details from U.S.-based epidemiologic studies examining associations between wildfire smoke exposure and respiratory and cardiovascular-related health effects and mortality.**

| Study; Location; Fire Yr | Health Outcomes (Ages) | Exposure Indicator Avg Time | Types of Air Quality Data Used | Exposure Assessment Methodology |
|---|---|---|---|---|
| Zu et al. (2016);<br>New York, NY; Boston, MA;<br>July 2002 Quebec Wildfires<br>(July, 2001−2003) | Total (nonaccidental)<br>(All) | $PM_{2.5}$ | Monitored | Daily average $PM_{2.5}$ concentrations across all monitors in Boston and each borough in New York. |

AIRACT-4 = Air Indicator Report for Public Awareness and Community Tracking; AMI = acute myocardial infarction; AOD = aerosol optical depth; avg = average; CHF = congestive heart failure; CMAQ = Community Multiscale Air Quality; COPD = chronic obstructive pulmonary disease; CV = cross-validation; CVD = cardiovascular disease; ED = emergency department; FCMAQ = fused-CMAQ; FEM = Federal Equivalent Method; FRM = Federal Reference Method; GBM = Generalized Boosting Model; GEOS-Chem = Goddard Earth Observing System with a global chemical transport model; GWR = geographically weighted regression; HA = hospital admissions; HF = heart failure; HMS = Hazard Mapping System; HYSPLIT = Hybrid Single-Particle Lagrangian Integrated Trajectories; IHD = ischemic heart disease; MAIAC = Multiangle Implementation of Atmospheric Correction algorithm; max = maximum; MI = myocardial infarction; MODIS = Moderate Resolution Imaging Spectroradiometer; NOAA = National Oceanic and Atmospheric Administration; OHCA = out-of-hospital cardiac arrest; PE = pulmonary embolism; PVD = peripherial vascular disease; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; $PM_{2.5}$ Tot = monitored $PM_{2.5}$ data; $PM_{2.5}$ TotCMAQ = $PM_{2.5}$ estimated using CMAQ; $PM_{2.5}$ TotCMAQ-M = $PM_{2.5}$ estimated using CMAQ in locations and times with monitoring data; SABA = short-acting β2 agonists; SFS = Smoke Forecasting System; TIA = transient ischemic attack; URIs = upper respiratory tract infections; WFEIS = Wildland Fire Emissions Information System; WRF-Chem = Weather Research and Forecasting Model with Chemistry; yr = year; ZCTA = ZIP-code tabulation areas.

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## A.6.2. Supplemental Information for Section 6.3

A literature review was conducted to identify published studies that provide data on individual and community actions to reduce wildfire smoke exposure. The literature review was limited to studies published from 2005 to May 2020 with keywords that included wildfire/prescribed fire and smoke, $PM_{2.5}$, and exposure, along with terms for actions/interventions (e.g., air filtration). Although several hundred published studies were identified with the search terms, after reviewing the titles and abstracts only 243 publications were determined to be relevant to wildfire or prescribed fire smoke exposure. Of those, 26 specifically addressed some aspect of smoke exposure mitigation and were included in the discussion within Section 6.3 of CHAPTER 6.

In order to be most informative in assessing the potential implications of public health messaging campaigns that attempt to reduce/mitigate population exposure to wildfire smoke around the case study areas, studies were limited to those conducted in the U.S. and Canada, with a few exceptions. Only three publications were identified that surveyed the likelihood of taking action to reduce wildfire smoke exposure in North America, so the literature review was expanded to include studies that were published before 2005 and from other parts of the world. Two additional studies were included, one published in 2002 conducted in North America and one conducted in Australia. In addition, the only published study with data on the effectiveness of staying indoors with windows and doors closed was conducted in Australia and also was included.

## Table A.6-2 Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. μg/m$^3$ |
|---|---|---|---|---|
| *Behavioral Changes—Avoid Outdoor Activity* | | | | |
| Rappold et al. (2019) | Avoided outdoor activity | 61 | SmokeSense App users with no reported health history and no symptoms | NR 1 |
| | | 6 | SmokeSense App users reported health history | |
| | | 90 | SmokeSense App users experiencing four or more symptoms | |
| Richardson et al. (2012) | Avoided outdoor recreation | 78 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$<br>(Daily) = 82.9<br>(Hourly) = 223 |
| Sugerman et al. (2012) | Did not play sports outside | 88 | Residents of San Diego County during the 2007 San Diego Fires | $PM_{2.5}$ 2 (daily) >128 for 10 days<br>Maximum $PM_{2.5}$ (daily) = 803.1<br>Mean $PM_{2.5}$ (daily) = 89<br>(Hutchinson et al., 2018) |
| Kolbe and Gilchrist (2009) | Reduced outdoor activities | 54 | Residents of Albury, New South Wales, Australia during 2003 bush fires | $PM_{2.5}$ 2 (daily) >128 for 9 days<br>Maximum $PM_{2.5}$ 2 (daily) = 597 |

**Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.**

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. μg/m$^3$ |
|---|---|---|---|---|
| *Behavioral Changes—Stayed Inside/Closed Doors and Windows* | | | | |
| Rappold et al. (2019) | Stayed indoors | 68 | SmokeSense App users with no reported health history and no symptoms | NR 1 |
| | | 70 | SmokeSense App users reported health history | |
| | | 90 | SmokeSense App users experiencing four or more symptoms | |
| Richardson et al. (2012) | Stayed inside | 73 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |
| Sugerman et al. (2012) | Stayed inside | 59 | Residents of San Diego County during the 2007 San Diego Fires | $PM_{2.5}$ 2 (daily) >128 for 10 days<br>Maximum $PM_{2.5}$ (daily) = 803.1<br>Mean $PM_{2.5}$ (daily) = 89<br>(Hutchinson et al., 2018) |
| | Kept windows closed | 76 | | |
| Kolbe and Gilchrist (2009) | Closed windows and doors | 44 | Residents of Albury, New South Wales, Australia during 2003 bush fires | $PM_{2.5}$ 2 (daily) >128 for 9 days<br>Maximum $PM_{2.5}$ 2 (daily) = 597 |
| Mott et al. (2002) | Stayed inside | 79 | Residents of Hoopa, CA during 1999 wildfire that were aware of public service announcements on smoke impacts | $PM_{2.5}$ 2 (daily) >128 for 15 days<br>$PM_{2.5}$ 2 (daily) >425 for 2 days |

**Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.**

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. µg/m$^3$ |
|---|---|---|---|---|
| *Behavioral Changes—Evacuated* | | | | |
| Rappold et al. (2019) | Left area | 30 | SmokeSense App users with no reported health history and no symptoms | NR 1 |
| | | 40 | SmokeSense App users reported health history | |
| | | 65 | SmokeSense App users experiencing four or more symptoms | |
| Richardson et al. (2012) | Evacuated | 5.6 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |
| Kolbe and Gilchrist (2009) | Travelled out of area | 14 | Residents of Albury, New South Wales, Australia during 2003 bush fires | $PM_{2.5}$ 2 (daily) > 128 for 9 days<br>Maximum $PM_{2.5}$ 2 (daily) = 597 |
| | | 12 | Residents of Albury, New South Wales Australia during 2003 bush fires who saw, heard, or read smoke advisory | |
| Mott et al. (2002) | Evacuated area during smoke | 48 | Residents of Hoopa, CA during 1999 wildfire | $PM_{2.5}$ 2 (daily) >128 for 15 days<br>$PM_{2.5}$ 2 (daily) >425 for 2 days |
| | | 35 | Residents of Hoopa, CA during 1999 wildfire that were aware of public service announcements on smoke impacts | |
| | | 44 | Residents of Hoopa, CA during 1999 wildfire without a pre-existing condition | |
| | | 58 | Residents of Hoopa, CA during 1999 wildfire with a pre-existing condition | |

Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. $\mu g/m^3$ |
|---|---|---|---|---|
| *Exposure Reduction—Ran HVAC system* | | | | |
| Richardson et al. (2012) | Ran air conditioner more than usual | 60 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |
| Sugerman et al. (2012) | Used home air conditioner | 16 | Residents of San Diego County during the 2007 San Diego Fires | $PM_{2.5}$ 2 (daily) >128 for 10 days<br>Maximum $PM_{2.5}$ (daily) = 803.1<br>Mean $PM_{2.5}$ (daily) = 89<br>(Hutchinson et al., 2018) |
| *Exposure Reduction—Used Air Cleaner* | | | | |
| Rappold et al. (2019) | Ran an air cleaner | 30 | SmokeSense App users with no reported health history and no symptoms | NR 1 |
| | | 52 | SmokeSense App users reported health history | |
| | | 86 | SmokeSense App users experiencing four or more symptoms | |
| Richardson et al. (2012) | Used an air cleaner | 21 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |

**Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.**

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. μg/m³ |
|---|---|---|---|---|
| Sugerman et al. (2012) | Used HEPA cleaner | 10 | Residents of San Diego County during the 2007 San Diego Fires | $PM_{2.5}$ 2 (daily) >128 for 10 days<br>Maximum $PM_{2.5}$ (daily) = 803.1<br>Mean $PM_{2.5}$ (daily) = 89 (Hutchinson et al., 2018) |
| Mott et al. (2002) | Used HEPA cleaner | 34% | Residents of Hoopa, CA during 1999 wildfire | $PM_{2.5}$ 2 (daily) >128 for 15 days<br>$PM_{2.5}$ 2 (daily) >425 for 2 days |
| | | 26% | Residents of Hoopa, CA during 1999 wildfire without a pre-existing condition | |
| | | 52% | Residents of Hoopa, CA during 1999 with a pre-existing condition | |
| *Exposure Reduction – Used Respirator/Mask* | | | | |
| Rappold et al. (2019) | Wore a respirator | 14 | SmokeSense App users with no reported health history and no symptoms | NR 1 |
| | | 24 | SmokeSense App users reported health history | |
| | | 80 | SmokeSense App users experiencing four or more symptoms | |
| Richardson et al. (2012) | Wore a mask | 7 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |
| Mott et al. (2002) | Wore an N95 mask | 10 | Residents of Hoopa, CA during 1999 wildfire | $PM_{2.5}$ 2 (daily) >128 for 15 days<br>$PM_{2.5}$ 2 (daily) >425 for 2 days |

**Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.**

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. µg/m$^3$ |
|---|---|---|---|---|
| *Symptom Mitigation—Took Medicine* | | | | |
| Kolbe and Gilchrist (2009) | Increased regular medication | 1.6 | Residents of Albury, New South Wales, Australia during 2003 bush fires | $PM_{2.5}$ 2 (daily) >128 for 9 days<br>Maximum $PM_{2.5}$ 2 (daily) = 597 |
| | | 2.3 | Residents of Albury, New South Wales, Australia during 2003 bush fires who saw, heard, or read smoke advisory | |
| Richardson et al. (2012) | Took medicine | 13 | Residents of five cities within the vicinity of Station Fire in southern California | Maximum $PM_{2.5}$ (daily) = 82.9 (hourly) = 223 |
| *Messaging Effectiveness* | | | | |
| Mott et al. (2002) | Took exposure reduction action due to PSA | 66 | Residents of Hoopa, CA during 1999 wildfire | $PM_{2.5}$ 2 (daily) >128 for 15 days<br>$PM_{2.5}$ 2 (daily) >425 for 2 days |
| Kolbe and Gilchrist (2009) | Changed behavior due to messaging | 43 | Residents of Albury, New South Wales, Australia during 2003 bush fires | $PM_{2.5}$ 2 (daily) >128 for 9 days<br>Maximum $PM_{2.5}$ 2 (daily) = 597 |

## Table A.6-2 (Continued): Likelihood of taking actions to reduce wildfire smoke exposure reported in recent studies.

| Study | Exposure Reduction Action | Percent Population Taking the Action | Population Characteristics | Outdoor PM Concentration. μg/m$^3$ |
|---|---|---|---|---|
| Sugerman et al. (2012) | Took at least one action from messaging | 98 | Residents of San Diego County during the 2007 San Diego Fires | $PM_{2.5}$ 2 (daily) > 128 for 10 days<br>Maximum $PM_{2.5}$ (daily) = 803.1<br>Mean $PM_{2.5}$ (daily) = 89 (Hutchinson et al., 2018) |
| | Took all actions from messaging | 27 | | |

HEPA = high-efficiency particulate air; HVAC = heating, ventilation, and air conditioning; NR = $PM_{2.5}$ concentrations not reported; PM = particulate matter; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 μm; PSA = public service announcement.

Note: $PM_{2.5}$ calculated assuming 85% of $PM_{10}$ concentration (Lutes, 2014).

**Table A.6-3 Percent reduction in $PM_{2.5}$ concentrations associated with actions/interventions reported in recent studies.**

| Study | Intervention | Percent $PM_{2.5}$ Reduction | Description of Comparison | Outdoor $PM_{2.5}$ Concentration. μg/m$^3$ |
|---|---|---|---|---|
| *Residential Measurement Studies* | | | | |
| U.S. EPA (2018) Table 4 [*From* Park et al. (2017)] | Portable air cleaner with HEPA filter | 43[a] | Eight homes in California with HEPA filters with activated carbon; eight homes without; 12-week intervention | |
| U.S. EPA (2018) Table 5 [*From* Allen et al. (2011)] | Portable air cleaner with HEPA filter | 60 | 25 homes in British Columbia with HEPA filters during half of study period and without HEPA filters during rest; 1-week intervention | 11.2 (mean) |
| U.S. EPA (2018) Table 5 [*From* Weichenthal et al. (2013)] | Portable air cleaner with electrostatic precipitator | 61 | 20 homes in Manitoba, Canada with Filtrete electrostatic filters during half of study period and without filters during rest; 1-week intervention | 42.5 |
| U.S. EPA (2018) Table 5 [*From* Kajbafzadeh et al. (2015)] | Portable air cleaner with HEPA filter | 40 | 20 woodsmoke impacted homes in Vancouver with HEPA filters during half of study period and without HEPA filters during rest; 1-week intervention | 5.0 HEPA off<br>3.9 HEPA on |
| Barn et al. (2008) Table 2 | Portable air cleaner with HEPA filter | 57.7 | 26 homes in British Columbia during forest fire (summer) or wood smoke (winter); 1 day each with and without filter | 3−91 (S)<br><4−189 (W) |
| Henderson et al. (2005) Figure 7 | ESP air cleaners | 63−88 | Eight homes in Colorado during wildfire or prescribed fire; paired homes with and without air cleaners | 6−38 (outside during fire) |
| Singer et al. (2017) Table 2 | HVAC with MERV13 at return (E) | 88−93 | Single test house in California; Reference system = HVAC MERV4 at return had 65−75% reduction | 6−16 (S)<br>8−31 (F/W) |
| | HVAC continuous with MERV16 at supply (C) | 96−97 | | |

**Table A.6-3 (Continued): Percent reduction in $PM_{2.5}$ concentrations associated with actions/interventions reported in recent studies.**

| Study | Intervention | Percent $PM_{2.5}$ Reduction | Description of Comparison | Outdoor $PM_{2.5}$ Concentration. µg/m$^3$ |
|---|---|---|---|---|
| | Portable air cleaner with HEPA | 90−94 | | |
| Alavy and Siegel (2020) Figure 3 | HVAC with MERV8, MERV11, MERV14 | 16 MERV8<br>36 MERV8E<br>45 MERV11E<br>41 MERV14E | 21 residences in Toronto; in situ effectiveness compared to system off or no filter | |
| Reisen et al. (2019) Table 2 | Window/door open | 12[b] | Home: ~98 yr old, 8 windows, 4 doors; air conditioner (H10) | 335.8 (h max.) |
| | Windows open | 56.7[b] | Home: 8 yr old, 16 windows, 4 doors; air conditioner (H11) | 386.5 (h max.) |
| | Windows/door open | 38.5[b] | Home: 28 yr old, 4 windows, 2 doors; air conditioner (H12) | 56.1 (h max.) |
| | Closed | 48.5[b] | Home: ~30 yr old, 8 windows, 3 doors; air conditioner (H16) | 56.0 (h max.) |
| | Windows open 20−60% of time during wood smoke event | 67.5−75.7[b] | Home: ~23 yr old, 14 windows, 4 doors; air conditioner (H21) | |

**Table A.6-3 (Continued): Percent reduction in $PM_{2.5}$ concentrations associated with actions/interventions reported in recent studies.**

| Study | Intervention | Percent $PM_{2.5}$ Reduction | Description of Comparison | Outdoor $PM_{2.5}$ Concentration. $\mu g/m^3$ |
|---|---|---|---|---|
| *Residential Modeling Studies* | | | | |
| Fisk and Chan (2017b) Table 5 | HVAC fan (continuous), low efficiency filter (i1) | 24 | Comparator: Home with intermittent operating HVAC system with typical low-efficiency particle filter (home B1 mean = 29.2 $\mu g/m^3$) | 56.9 |
| | HVAC fan (continuous), high efficiency filter (i2) | 47 | | |
| | HVAC fan (intermittent), high efficiency filter (i3) | 11 | | |
| | HVAC fan (continuous), low efficiency filter, continuous portable air cleaner (i4) | 51 | | |
| | HVAC fan (continuous), high efficiency filter, continuous portable air cleaner (i5) | 62 | | |
| | No forced air system, continuous portable air cleaner (i6) | 45 | Comparator: Home with no HVAC, may have moderate window AC (home B2 mean = 31.9 $\mu g/m^3$) | |
| *Office Building Measurement Studies* | | | | |
| Stauffer et al. (2020) Table 4 | Portable air cleaner | 73 (day) 92 (night) | Offices with and without portable air cleaners during day and night during wildfire season | 17.5 |
| Pantelic et al. (2019) Figure 5 and text page 10 | HVAC system with filters | 60[c] | Office building with HVAC system with filters (MERV8, Gas Phase filter, and MERV13) compared with an office building with natural ventilation system | 70 (4th St) 53 (Wurster) |

## Table A.6-3 (Continued): Percent reduction in $PM_{2.5}$ concentrations associated with actions/interventions reported in recent studies.

| Study | Intervention | Percent $PM_{2.5}$ Reduction | Description of Comparison | Outdoor $PM_{2.5}$ Concentration. µg/m$^3$ |
|---|---|---|---|---|
| *Modeling Studies Residential and Other Buildings* | | | | |
| Fisk and Chan (2017a) Table S8 and S9. | Home HVAC MERV6 running 30% of time (i1a, i1b) | 2−4 | Comparison:<br>Home: HVAC MERV 6 operating 15−20% of the time, no HEPA portable air cleaner<br>Other buildings: MERV8 | 11.4 (LA)<br>10.0 (NJ)<br>10.4 (TX) |
| | Home HVAC MERV6 running 30−40% of time, HEPA portable air cleaner (i5a, i5b) | 27$^{-3}$1 | | |
| | Home: HEPA portable air cleaner (i4) | 26$^{-3}$0 | | |
| | Homes: HVAC MERV6 running 15−20% of time, HEPA portable air cleaner<br>Other buildings: MERV13 (i8) | 7−9 | Comparison:<br>Home: HVAC MERV 6 operating 15−20% of the time, no HEPA portable air cleaner<br>Other buildings: MERV8 | |

AC = air conditioning; ESP = electrostatic precipitator; HEPA = high-efficiency particulate air; HVAC = heating, ventilation, and air conditioning; $PM_{2.5}$ = particulate matter with a nominal mean aerodynamic diameter less than or equal to 2.5 µm.

[a]Based on average $PM_{2.5}$ concentration difference between groups.

[b]Based on maximum hourly $PM_{2.5}$.

[c]Calculated as percent difference in median I/O ratios.

## A.7. SUPPLEMENTAL INFORMATION FOR CHAPTER 7

1 No supplemental information.

## A.8. SUPPLEMENTAL INFORMATION FOR CHAPTER 8

**Table A.8-1 Corresponding table of estimated wildfire-$PM_{2.5}$ illnesses (95% confidence interval) from sensitivity analyses presented in Figure 8-1 and Figure 8-2.**

| Case Study | Scenario | Asthma ED Visits | Hospital Admissions | |
|---|---|---|---|---|
| | | | Respiratory | Cardiovascular |
| Timber Crater 6 (TC6) | Actual Fire | 0.4 (0.31 to 0.5) | 0.17 (0.01 to 0.31) | 0.07 (−0.01 to 0.14) |
| | Scenario 1 (small) | 0.24 (0.19 to 0.28) | 0.1 (0.01 to 0.18) | 0.04 (−0.01 to 0.09) |
| | Scenario 2a (large) | 1.5 (1.2 to 1.8) | 0.69 (0.05 to 1.3) | 0.26 (−0.05 to 0.55) |
| | Scenario 2b (largest) | 2.3 (1.8 to 2.7) | 1.1 (0.08 to 1.9) | 0.41 (−0.09 to 0.87) |
| | Prescribed Fires | 0.07 (0.05 to 0.08) | 0.03 (0 to 0.06) | 0.01 (0 to 0.02) |
| Rough Fire | Rough Fire (actual) | 100 (83 to 120) | 40 (2.3 to 74) | 15 (−3.2 to 32) |
| | Rough Fire (Scenario 1) | 62 (50 to 74) | 24 (2 to 44) | 8.6 (−1.85 to 19) |
| | Rough Fire (Scenario 2) | 110 (85 to 120) | 42 (3 to 77) | 16 (−3.4 to 33) |
| | Sheep Complex Fire | 15 (12 to 18) | 5.4 (0.4 to 10) | 2 (0.4 to 4) |
| | Boulder Creek Fire (proposed prescribed fire) | 2.7 (2.1 to 3.2) | 0.9 (0.06 to 1.7) | 0.3 (−0.007 to 0.7) |

ED = emergency department; TC6 = Timber Crater 6.

## A.9. SUPPLEMENTAL INFORMATION FOR CHAPTER 9

No supplemental information.

## A.10. REFERENCES

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